MEASURING PRICE SENSITIVITY:
A MODEL OF CONSUMER PRICE INERTIA

By

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Abstract of Dissertation Presented to the Graduate School
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MEASURING PRICE SENSITIVITY: A MODEL OF CONSUMER PRICE INERTIA

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This dissertation proposes price inertia, the tendency of consumers to restrict purchases in a product category to brands in the same price range, as a unifying construct that integrates recent research on reference prices and market structure defined by price tiers. The model specifies heterogeneity among consumers in terms of differences in acceptable price ranges, allowing for a variety of patterns of aggregate price sensitivities to be empirically determined. The model helps resolve the apparent contradiction between the assumption of reference price models of vigilant tracking of brand prices by all consumers and the findings of descriptive survey research that reveal poor price knowledge at the brand level for many consumers.

An exploratory random telephone survey of consumers in Florida found prima facie evidence for the assumption of the model of the existence of acceptable price ranges for six product categories. A majority of consumers had upper bounds on the acceptability of prices for frequently purchased product categories that were within the range of observed prices.

An extensive analysis of scanner panel data established that the price tier variable specified by the model of consumer price inertia was a significant influence on brand choice for all three product categories examined. Probability of purchasing a brand increased significantly as a function of the membership of the price of the brand in the range of acceptable prices for the consumer, even after accounting for tendencies to restrict purchases to a small set of brands, a small set of sizes, and main effects of price and promotion. The effect of price inertia dominated that of reference price for one product category, and was comparable or slightly better for the other two categories. There was little difference between the two measures in terms of predictive validity for a holdout sample. Price, promotion and consideration set membership defined as the set of items purchased in the recent past were the strongest and most consistent predictors of brand choice.

The model of consumer price inertia points to the deleterious long term effects of frequent category-wide price promotions on consumer price sensitivity.

CHAPTER 1
INTRODUCTION

The Vicious Cycle of Price Promotions

The Growing Importance of Price Promotions

There is growing evidence about the increasing allocations to price related promotions in the total budget for promotions of consumer goods companies. Abraham and Lodish (1987) estimate the percentage of sales volume on "deal" to be over 90% in many consumer goods categories. The Twelfth Annual Survey of Promotional Practices (1989) of the Donnelley Marketing Company indicates that the percentage of the budget for promotions allocated to consumer promotions increased from 19% to 27% over 1976-1989. Blattberg and Neslin (1990) cite various sources for other evidence that the importance of price-related promotions is increasing, at an accelerating rate. The distribution of coupons increased at an annual rate of 10.4% between 1977 and 1988. The percentage of sales in department stores from markdowns increased from 6.0% in 1963 to 19.3% in 1986. Sales promotion expenditures grew at an annual rate of 12% over 1976-1986.

The Resultant Impact on Consumer Price Sensitivity

The impact of this increased manufacturer attention to price-related promotions on consumers is further enhanced by the increased importance of channel members in delivering the product to the consumer. As brands proliferate, there is increased competition for shelf space, which is controlled by the retailer. Retail advertisements at the brand level tend to emphasize price over all other attributes, and in the process, attune the consumer to price differences. There has also been an increasing tendency for stores to carry their own brands and generic alternatives and sell them aggressively, positioned against name brands primarily on price. This helps further emphasize the commonality of all brands on non-price dimensions. Finally, growing regulatory concern has made it necessary for retailers to display prices, and often, unit prices, prominently, making it easier for consumers to use price information.

The combined effect of these conditions is to increase the motivation, ability and opportunity of the consumer to use price information in making purchase choices, and, hence, for consumer price sensitivity to be on the rise. Both manufacturers and retailers, perhaps in reaction to this increased sensitivity, have engaged in price cutting wars that have only served to accelerate rather than stem this trend.

Measuring Consumer Price Sensitivity

Interestingly, the last decade has also seen an increased interest among marketing researchers, especially among empirical modellers, in measuring consumer price sensitivity and in understanding the determinants of price competition in the marketplace in terms of the underlying market structure. This has partly been a reaction to the increasing use of price promotions by consumer goods companies. More importantly, the availability of large volumes of detailed data at the Universal Product Code (UPC) level from suppliers of single source scanner data has helped make models of choice behavior and market structure estimable at the household level, and to be subjected to powerful statistical tests.

The fundamental motivation for this dissertation is the idea that this increased attunement of consumers to these pervasive price stimuli calls for rethinking of the manner in which we specify models of choice, and in particular, of the manner in which we specify the effects of price. For example, much extant modelling research on consumer choice behavior has the brand as the unit of analysis, and hence the focus of model assumptions. Thus, we see the emphasis given to brand names in the specification of consideration sets (Grover and Srinivasan 1987; Zenor 1989), and of variables like variety-seeking (Givon 1984) or brand loyalties (e.g. Guadagni and Little 1983; Kalwani et al 1990; Lattin and Bucklin 1988) that control for individual differences among consumers.

This dissertation will argue that this emphasis could well be replaced, or at least augmented, by an emphasis on price with similar, or even, better levels of fit

and predictive power. Consider, for example Zenor (1989) who analyzed the market structure for dishwashing detergents as an overlapping structure of the consideration sets of different segments. The segmentation scheme included a segment that was "loyal" to the generic alternative. It is surely more plausible to interpret, and hence model this segment's choice behavior as extremely price sensitive, and driven by an attachment to low prices rather than as a consequence of "loyalty" to generic alternatives. Similarly, Grover and Srinivasan (1987) segment consumers based on switching probabilities. Under such a scheme, consumers who switch between two brands to satisfy a variety-seeking need would be classified into the same segment as price-conscious consumers who switch to take advantage of price promotions, making for a behaviorally heterogeneous segment.

In situations in which prices and promotional levels remain stable for all brands, it is virtually impossible to distinguish on the basis of purchase behavior, whether a consumer who constantly purchases the same alternative is in fact "brand" loyal, or "price" loyal to some point on the price continuum. In situations in which there is activity in price and promotion levels, the specification of a model with emphasis on either brand or price can lead to alternate interpretations of the market structure. In this dissertation, we explore this possibility by developing an alternative to current models of brand choice behavior that emphasizes response to price.

Another outcome of this emphasis of previous research on brand names in specifying models of choice is that differences in price sensitivities among consumers are rarely specified, probably in the interests of parsimony (Fader and McAlister

1990, and Zenor 1989 are exceptions). A fundamental hypothesis of this dissertation is that just as measures that account for prior repetitive purchases of certain brands (measures that loosely measure brand loyalty) are useful predictors of brand choice, so can summary measures of prices previously paid in a product category be useful indicators of responses to price and price changes. It will be argued that specifying individual differences in price sensitivity is key to understanding the overall impact of price and price changes on market share.

Objectives of Dissertation

The objectives of this dissertation are

- to offer a broad and general conceptualization of consumer price sensitivity
- to review recent research on price effects that seems to reflect the changing role of price in influencing consumer choice and brand competition
- to propose a model that integrates the findings of this previous research and is consistent with the offered conceptualization of price sensitivity
- to estimate and validate the model for survey data and for purchase data from different product categories
- to examine the theoretical, methodological and substantive implications of the empirical findings.

In this, the introductory chapter, I explore the meaning of price sensitivity in conceptual terms. The second chapter is a review of past literature on the effects of price on choice. Chapter 3 presents a discussion of the proposed model of consumer

price inertia. Chapter 4 describes the findings of a random sample survey that was carried out to assess the prima facie evidence for the model's assumptions. Chapter 5 describes the calibration and estimation of the model of consumer price inertia on three scanner panel datasets. Chapter 6 summarizes the contributions and limitations of the research, and indicates areas for future research.

A Conceptualization of Price Sensitivity

Consider the following supermarket scenario:

A consumer enters the detergents aisle of the supermarket and reaches for TIDE, the brand of detergent that she usually purchases. She notices that the price of the 12 oz. carton (the usual sized package she buys) is $1.69. She replaces the package and buys a larger 24 oz. package for $3.09. As she is leaving the aisle, she notices a large display of SCOTT paper towels at the end of the aisle, with a sign that says "CONSUMER BONUS - SALE PRICE 49 CENTS REG PRICE 69 CENTS." She picks up four rolls. In the next aisle, she picks up a six-pack of her favorite BARTLES AND JAYMES PEACH wine-cooler without checking its price (which incidentally is $3.99), and further down the aisle, compares the prices of COKE ($1.99 for a six-pack) and PEPSI ($1.89 for a six-pack) and picks up a six-pack of PEPSI. Also prominently displayed in the same aisle is PUBLIX cola (the store brand--priced at $1.59 for a six-pack). Finally, as she is waiting to check out her purchases, she notices a display for HERSHEY's Golden Almond Chocolate, by the

side of the register. A sticker at the display says "New Product - 3 for $1.00." She picks up two candy bars.

The consumer in the above scenario displayed a wide variety of behavioral responses to price and promotion information. In different product classes, she exhibited varying degrees of sensitivity to price. She ignored price information for the winer coolers, she used price to choose between brands of cola, to decide the size of detergent to be purchased, and she tried a candy bar. Similarly, it may be expected that within a product category, different consumers may be affected in very different ways by price information. Further, even for the same consumer, within a product category, price changes of different brands may affect the consumer differently; in the example above, the consumer ignored price information for the store brand, but seemed to react to price information for the national brands of colas.

Price sensitivity can thus connote several meanings. A consumer may be referred to as price sensitive if she is "aware" or "conscious" of prices as she is shopping, or if she has knowledge of prices of different brands, or if she uses price to infer quality and hence prefers higher priced brands, or if she uses price to choose between brands or sizes, or to decide when and whether to purchase and consume in one product category versus a substitute category, or in the extreme, decides how much to consume of a product category. Thus, price information may influence the choice process through a variety of intermediate influences, only some of which are reflected in purchase behavior.

Some of these meanings have been explored by both descriptive and theoretical research in marketing and consumer behavior in the past, as listed below.

(i) Price awareness, in terms of price consciousness and price recall at the time of purchase has been the subject of studies such as Dickson and Sawyer (1990) (see also Dickson and Sawyer (1986) for a review of previous studies).

(ii) Price knowledge has been studied by Krishna, Currim and Shoemaker (1991) who examined the extent of knowledge of regular and deal prices of supermarket shoppers.

(iii) The tendency of consumers to make inferences about quality from price information has been the subject of numerous studies (Olson [1977] and Monroe and Petroshius [1981] have excellent reviews of this research.)

(iv) The effects on brand choice have been modelled in several articles, especially in the recent past (e.g. Guadagni and Little 1983; Kalwani, Yim, Sugita and Rinne 1990; Lattin and Bucklin 1989; Winer 1986).

(v) The effects of price on quantity purchased was the subject of Blattberg, Eppen and Lieberman (1981), Gupta (1988), and Krishnamurthi and Raj (1988,1991).

(vi) The hypothesis that short term price related promotions lead to accelerated purchase decisions has been explored by research such as Gupta (1988) and Neslin, Henderson and Quelch (1985).

While it is important to recognize the effect of price at these intervening stages of the consumer choice process, it is the effect on discrete brand choice that has the most relevance for understanding the structure of brand competition, and the

manner in which price competition affects and is affected by market structure. Also, Gupta (1988) concluded that 84% of the sales increase due to promotion comes from brand switching. Finally, considering the impact of prices on these intermediate stages is important for models of choice only when there are individual differences in these intervening sensitivities. It will be argued later that the most significant differences among consumers in terms of these sensitivities is (or at least is reflected in) the extent to which price predominates over the brand name in the "consideration set" and choice decisions. That is, whether or not consumers consider price in forming the consideration set might account for much of the variance in aggregate sales or market share that is explained by price sensitivities. For all these reasons, this dissertation will focus on the effect of price on discrete brand choice.

A working "behavioristic" definition of price sensitivity that will be adopted is "a consumer is said to be price sensitive if a change in the price of at least one brand in the marketplace leads to a change in her brand choice behavior." The definition does not require consumers to remember or recall prices. All that it requires is for the consumer's behavior to reflect reaction to price changes in the marketplace.

It may be noted also that all consumers are price sensitive in some sense of the definition. If the price of a brand (or all brands in a category) keeps increasing or keeps decreasing over time, eventually, every consumer may be expected to drop out of or into the market for the brand (or product category). It is the amount of change that is required for the consumer to change her behavior that defines the extent of the consumer's price sensitivity. Accounting for differences in the extent

of this sensitivity across consumers, and then determining the overall market response to a change in the price environment may lead to the best predictive models of brand choice.

It may also be noted that the definition does not only include persons who react positively to price decreases; it also includes persons who react negatively to price decreases e.g. consumers who mistrust "sales," inferring that only low quality items are put on sale. The definition is thus reflective of the effect of price on the intermediate "inference" stage.

Finally, the definition stresses the fact that it is only under conditions of price changes that one can measure price sensitivity. While the point may appear rather obvious, it is possible that the traditional emphasis on brand names as the unit of analyzing market share movements may have camouflaged the effects of prices. A common treatment of brand loyalty in the past has been to observe the sequence of brand choices and create indices that indicate the extent of loyalty to various brands (e.g. Guadagni and Little 1983; Kalwani et al 1990; Lattin and Bucklin 1989). A string of purchases of brands X and A such as XXXXXAXXXXXX would be classified as indicative of a brand loyal consumer under many such schemes. Now if the sequence of prices of brand X over this run of purchases had been PPPPPQPPPPPP, with Q higher than P (and the price of A lower than Q), the same run may indicate a price sensitive consumer, at least in terms of our definition. It is only in the recent past that modellers have recognized such effects and have made conscious efforts to correct for such effects (e.g. Kamakura and Russell 1989).

Similarly a string of purchases such as XXXXXXXXXXX cannot be classifed as indicative of brand loyalty unless the price of brand X changed over the period of the run.

The proposed definition of price sensitivity also reflects the possibility that price changes may mean different things for the same brand for different consumers e.g. an increase of 10 cents in the price of brand X could affect some consumers but not others, and may mean different things for the same consumer for different brands e.g. an increase of 10 cents for brand X may affect a consumer differently than an increase of 10 cents for brand Y. Many current models of choice specify the same price sensitivity parameter for all the brands and for all consumers.

Thus, the definition emphasizes that in developing a measure of price sensitivity, it is crucial to recognize the interactive effects of brands, prices and individual differences in price sensitivities.

Our fundamental objective in developing a better measure of price sensitivity is to understand better the nature of competition among brands in the marketplace, so as to build more predictive power in determining market share changes as a function of price changes. Accordingly, we critically survey, in the next chapter, recent developments in the empirical modelling literature relating both individual choice probabilities and market share to price levels and price changes.

CHAPTER 2
LITERATURE REVIEW

The availability to academic researchers of large volumes of scanner data at the Universal Product Code (UPC) level and the pioneering Guadagni and Little (1983) article have led to tremendous growth in the marketing literature related to the effects of price on consumer choice. Two recent trends in the literature have been an emphasis on modelling the effects of past prices on current choice and on the possible role of price in structuring the market. A third trend has been the modelling of "non-compensatory" effects of price promotions on choice. These research streams are reviewed in that order, with respect to the light that they shed on consumer price sensitivity.

Modelling the Effects of Past Prices

Modelling the effects of lagged variables has a rich history in marketing in the analysis of the impact of advertising on sales and market share. Modelling the effects of past prices on choice and market shares has a more recent history. Different behavioral rationales for specifying effects of past prices of brands are discussed below.

The "self perception" effect was proposed by Dodson, Tybout and Sternthal (1978) who suggested that purchase of a brand on "deal" may indicate to an

introspective consumer that purchase was motivated by the price decrease rather than a preference for the brand itself (i.e. on nonprice attributes). Hence, when the price of the brand returned to pre-sale levels, the consumer would infer that her preference for the brand was weak, and would switch to another brand. Thus, the self perception effect suggests that previous purchase at a sale price would reduce the probability of purchase of a brand at the regular price at the current purchase occasion.

The "stockpiling" effect was hypothesized by Blattberg et al (1981) who developed a theory of inventory accumulation that predicted that certain kinds of consumers would tend to stockpile a brand (in accordance with the predictions of an inventory model) when it is on "deal," again leading to a prediction of lower market shares in weeks immediately succeeding a week in which a brand was on "deal."

The "expectations" effect has been the subject of the recent surge in research on the effects of reference prices (Gurumurthy and Little 1988; Kalwani, Yim, Rinne and Sugita 1990; Kalwani and Yim 1992; Lattin and Bucklin 1987; Raman and Bass 1988; Winer 1986) on consumer choice. The theory suggests that consumers develop expectations for prices of various brands and that they react to deviations from these expected prices. Again, the suggestion is that low prices in the past lead to expectations of low prices and hence to decreases in market shares when prices return to regular levels.

As outlined in the first chapter, the focus of this dissertation is on the effect of price on discrete brand choice, and hence the research on stockpiling is not

immediately relevant. There has been little sytematic effort to study the "self perception" effect on actual purchase data (Gurumurthy and Little 1988 is an exception). Also, the research on the effects of reference price offers the most exhaustive analysis of the effects of past prices at the brand level on current brand choice. Accordingly, we review in detail, in this section, only the research on the effects of reference prices.

Consider an experiment in which subjects repeatedly dip their hands into buckets of very cold water, and are then asked to judge the temperature level of a bucket of lukewarm water by feeling the water. Helson's adaptation level theory (1964) predicts that the repeated exposure to very low temperatures would create a low adaptation level for the judgment of temperature, as a consequence of which, the lukewarm water will be judged to be warmer than it would be under normal circumstances.

The notion that repeated exposure to a particular level of a certain stimulus creates "adaptation" around this level leading to increased sensitivity in the region of the adaptation level has been creatively exploited in consumer choice models seeking to incorporate the effects of past prices on current choice. The "price sensitivity" translation of the theory proposes that repeated exposure to a certain price for a brand causes the consumer to expect to find that price at each purchase occasion. Consequently, consumers react sharply to deviations from this expected price. As detailed later, some researchers in this stream (e.g. Gurumurthy and Little 1988) specified this expected price as a range rather than as a point. As long as prices lie

in the expected range, no change is expected in consumer response as the current stimulus is "assimilated" with the expected range. When price increases (or decreases) outside this range, the new price level is "contrasted" and produces significant negative (or positive) response to the brand.

Finally, Kahnemann and Tversky's (1979) prospect theory is invoked to suggest that when the encountered price is over the expected range, the difference is perceived as a loss, and when the encountered price is below the expected range, the difference is perceived as a gain. Prospect theory predicts that losses cause steeper or sharper responses than do gains. Consequently, the prediction is that increases in price over the expected range cause a greater perception of loss of utility than a similar "gain" when price decreases lead to a price that is below the expected range for the same amount of change. Thus, the effect of past prices is hypothesized to be through the creation of a "latitude of acceptance," deviations which lead to asymmetric changes in utility (see Figure 2.1).

While these effects have been hypothesized in previous reviews (Monroe 1973; Monroe and Petroshius 1981; Sawyer and Dickson 1984), it is only recently that models of choice/demand/market share have sought to incorporate these effects in specifications tested on purchase data (Gurumurthy and Little 1988; Kalwani et al 1990; Lattin and Bucklin 1989; Raman and Bass 1988; Winer 1986).

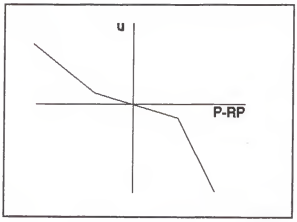

Figure 2.1 Asymmetric response to perceived "gains" and "losses"

While some or all of these psychological theories described are invoked in motivating reference price theory in these articles, these empirical exercises vary in their operationalizations of the model in interesting ways. One feature that is common to these exercises is the specification of forecasting rules from the economics literature to operationalize the measurement of reference price, as is discussed below.

Since many of the terms included in the specification of these models are similar, we define below common notation to be used in describing and evaluating these models:

u_{ijt} = utility of brand j for consumer i at choice occasion t

P_{ijt} = price of brand j facing consumer i at choice occasion t

RP_{ijt} = reference price of brand j for consumer i at choice occasion t

$PROB_{ijt}$ = probability of purchasing brand j for consumer i at occasion t

α_j = brand specific parameter indicating "attractiveness" of brand j (on non-price attributes) that is constant across consumers and purchase occasions.

Winer (1986). This paper investigates three brands of coffee for evidence of reference price effects, estimating a different binomial logit model for each of the brands. He specifies individual utility as

$$u_{ijt}=\alpha_j+\beta_1 PURCH_{ijt-1}+\beta_2 ADV_{ijt}+\beta_3 (RP_{ijt}-P_{ijt})+\beta_4 P_{ijt}+e_{ijt}, \qquad 2.1$$

where $PURCH_{ijt-1}$ is a dummy variable that takes value 1, if brand j was purchased by consumer i at the previous purchase occasion, and 0 otherwise, and ADV_{ijt} is the advertising exposure of consumer i to brand j, prior to occasion t. Hence, by the binomial logit specification,

$$PROB_{ijt}=\frac{e^{u_{ijt}}}{1+e^{u_{ijt}}}. \qquad 2.2$$

Rather than estimate a single multinomial model, a separate model is estimated for each brand, as different coefficients were probably expected to be estimated for the different brands. Hence, all the independent variables are measured in relative terms. For example, price of brand j is expressed as the ratio of the actual price of brand j to the average price of all the brands.

As reference price information is not coded in the panel database, some estimate of RP_{ijt} needs to be developed from the available data on past prices, etc.

Two different forecasting approaches from the economics literature were tested. Both approaches specify a point rather than a range for the reference price. An extrapolative expectations assumption specifies

$$RP_{ijt}=\delta_0+\delta_1 P_{ijt-1}+\delta_2 TREND_t+v_{ijt}, \qquad 2.3$$

where TREND is a variable that captures inflationary or deflationary tendencies in price levels and v_{ijt} is error. The reference price is thus predicted by the previous period's price adjusted for a trend.

The rational expectations model, usually attributed to Muth (1961), proposes that over lengths of time, economic agents "discover" the rules by which prices are set, so that they use the same rules to make predictions about future prices. Their predictions consequently are unbiased estimates of the actual price. The rules that Winer specifies for the rational consumer are

(1) firms set prices based on historical price levels, and,

(2) low share brands will seek to gain share in frequently purchased categories by cutting price. Consequently, Winer's specification for reference price based on rational expectations is

$$RP_{ijt}=\theta_0+\theta_1 P_{ijt-1}+\theta_2 MS_{jt-1}+\theta_3 TREND_t+v_{ijt}, \qquad 2.4$$

where MS_{ijt-1} is the market share of brand j at time (t-1). Since these predictions are expected to be unbiased estimates of the actual price, we should also have

$$P_{ijt}=RP_{ijt}+\mu_{ijt}, \qquad 2.5$$

where $E(\mu_{ijt})=0$.

Separately substituting 2.3 and 2.4 in 2.5 gives two models for estimating the parameter vectors δ and θ by OLS, as all the variables are now observed. These parameter estimates are then used to develop predicted values for RP_{ijt} (using 2.3 and 2.4) to be used in estimating the logit model (2.1 and 2.2). The results of these regressions for the estimation of RP_{ijt} are not reported.

The "reference price - observed price" difference in equation 2.1 has a significantly positive coefficient indicating support for Winer's hypothesis. It may be noted that asymmetry in responses to gains and losses is not tested. Little difference is observed in predictive power between the alternate expectation formulae. It is disconcerting to note though that the coefficient for the observed price for the rational expectations model is more than three times that for the extrapolative expectations model for two of the three brands. The coefficient of the difference between the expected and actual price is also very different for these two brands. It would be useful to compute and compare elasticities for the two different formulae for reference price. Winer does not believe that the data themselves support any one specification more than the other, though the rational expectations specification seems to indicate a much higher sensitivity to price. These differences raise the speculative question whether the more involved the model assumes the consumer to be with estimating prices, the more sensitive will he/she be shown to be by the estimates obtained.

Lattin and Bucklin (1989). The main point of departure from Winer's work in Lattin and Bucklin (1989) is the specification of reference points for both price and promotion. They propose that consumers also develop expectations about the promotional status of a brand. The effect of the reference point for promotion is specified as a threshold effect.

$$x_{ijt}=\lambda x_{ijt-1}+(1-\lambda)\,Z_{jt-1}, \qquad 2.6$$

where

x_{ijt} = consumer i's exposure level to promotional activity by brand j at purchase occasion t;

Z_{jt} = 1, if brand j was on promotion at occasion t;

= 0, otherwise;

λ = a smoothing parameter.

Further, PRP_{ijt} = 1, if $x_{ijt} \geq \theta$

= 0, if $x_{ijt} < \theta$,

where PRP_{ijt} = promotional reference point for consumer i for brand j at purchase occasion t (i.e. when the exposure to promotion exceeds the threshold θ, consumers expect the brand to be on promotion). Reference price is formulated as

$$RP_{ijt}=\lambda RP_{ijt-1}+(1-\lambda)\,P_{ijt-1}. \qquad 2.7$$

Note that this may be re-written as

$$RP_{ijt}=P_{ijt-1}+\lambda\,(RP_{ijt-1}-P_{ijt-1}). \qquad 2.8$$

(i.e. the previous period's price is adjusted for the "error" in the previous period's expectation). This predictive formula is referred to as the adaptive expectations model in the economics literature.

It may also be noted that Lattin and Bucklin have deterministic specifications for both reference price and promotional reference point. In the estimation, λ is deterministically set to 0 and to 0.7, the latter to approximate a "half-life" of two purchase occasions for the effect of promotional exposure. The parameter λ is assumed to be the same for both reference price and promotional exposure. The parameter θ is estimated by a grid search procedure. The utility specification used for the multinomial logit model is,

$$u_{ijt}=\alpha_j+\beta_1 BL_{ij}+\beta_2 LP_{ijt}+\beta_3 LPP_{ijt}+\gamma_0 Z_{ijt}+\gamma_1 P_{ijt}+\gamma_2 Z_{ijt}P_{ijt} +\delta_1 (P_{ijt}-RP_{ijt}) +\delta_2 (Z_{ijt}-PRP_{ijt}) +\epsilon_{ijt}. \quad (2.9)$$

BL, LP and LPP are included to account for individual differences in brand preferences. BL_{ij} is a brand loyalty specification and is measured as the proportion of occasions at which brand j was chosen by consumer i during an initialization period.

LP_{ijt} = 1, if brand j was purchased by consumer i at purchase occasion t-1,

= 0, otherwise.

LPP_{ijt} = 1 if brand j was purchased by consumer i on purchase occasion t-1 on promotion,

= 0, otherwise.

As λ is not estimated and θ is estimated through a grid search procedure for this arbitrarily chosen λ, it is difficult to interpret the results of the estimation procedure as a test of the reference point formation theory. The "Z-PRP" difference (i.e the difference between the actual and expected promotional status) is positive and significant as predicted. But strangely, the coefficient of the difference between the actual price and the reference price (P-RP) is positive and significant for $\lambda=0.7$, and positive and insignificant for $\lambda=0$. Lattin and Bucklin attribute this anomalous result to possible collinearity of the reference price variable with the reference promotional status. The correlation between RP and PRP range from -0.5 to -0.7 for the four brands of coffee investigated. Another explanation offered is that consumers may only buy their favored brand at low prices, with the result that they will always see other brands at their regular non-discounted prices. Thus, high RP might indicate low preference for the brand. The higher the RP, the lower should be P-RP, and the lower the utility for the brand. Hence, the coefficient of the difference might be positive. This explanation is less plausible because there are other variables that are already specified for the effects of these differences in brand preferences (like BL and LP).

Lattin and Bucklin do not comment on the negative non-significant coefficient for promotion Z. It is difficult to explain why current level of promotion is not a significant explanatory variable while "Z-PRP" is. Unlike Winer (1986), the coefficient for P is not very different for the two different reference price models. It

is -3.839 for $\lambda=0$ and -4.579 for $\lambda=0.7$. The "P-RP" coefficient is different though for these models (0.271 for $\lambda=0$; 1.004 for $\lambda=0.7$), and also incorrectly signed as discussed earlier.

The brand preference indicators BL and LP are significant and positive as expected. LPP is significant and negative as expected.

Lattin and Bucklin do not provide a compelling argument for why the process of promotional reference point formation might approximate a threshold effect. Similarly, the reference price specification is arbitrary. It is important to consider these issues as they suggest again that the way in which reference price is specified is likely to affect whether or not the "P-RP" difference is found to be significant.

An interesting finding in Lattin and Bucklin is a significant positive interaction between price and promotion, indicating, that promotions are more effective for higher priced brands. Given the nature of high consumer price involvement suggested by Lattin and Bucklin's model of reference price and promotional status, it might also be appropriate to specify interactions between "P-RP" and "Z-PRP", the degree to which the price exceeds the reference price and the degree to which the promotional status is unexpected (i.e. consumers would expect to see a price cut at the same time that they expect to see the brand on promotion).

Kalwani, Yim, Rinne and Sugita (1990). Kalwani et al (1990) depart from Winer (1986) in testing for asymmetry in the response to gains (when P-RP < 0) and losses (when P-RP > 0). They also provide a richer formulation for RP. The utility specification is

$$u_{ijt}=\alpha_j+\beta_1 BL_{ijt}+\beta_2 SL_{ijt}+\beta_3 Z_{ijt}+\beta_4 P_{ijt}+\beta_5 GAIN_{ijt}+\beta_6 LOSS_{ijt}+\epsilon_{ijt}, \quad 2.10$$

where $GAIN_{ijt} = RP_{ijt} - P_{ijt}$, if > 0, else 0,

and $LOSS_{ijt} = P_{ijt} - RP_{ijt}$, if > 0, else 0.

Like Guadagni and Little (1983), brand and size loyalty variables are included to control for individual differences in brand and size preferences. i.e.

$$BL_{ijt}=\delta_b BL_{ijt-1}+(1-\delta_b)\, LP_{ijt-1}, \quad 2.11$$

and size loyalty, SL is defined similarly. Z_{ijt} refers to promotion as before. Reference price is formulated as

$$RP_{ijt}=\gamma_0+\gamma_1 PASTPR_{ijt}+\gamma_2 FOP_j+\gamma_3 TREND_{ijt}+\gamma_4 DPC_i +\gamma_6 ST1_{ijt}+\gamma_7 ST2_{ijt}+\gamma_8 ST3_{ijt}+\mu_{ijt}, \quad 2.12$$

where

FOP_{ij} = frequency of promotion of brand j as encountered by consumer i and is expected to have a negative effect,

DPC_i = deal proneness of consumer i measured by the proportion of consumer i's purchases in the initialization period accompanied by a "deal" and is expected to have a negative effect, and

ST1, ST2 and ST3 are dummy variables for the store in which the purchase was made.

The variable PASTPR is defined following Helson (1964) as a weighted log mean of the prices encountered at the previous five purchase occasions, with more weight given to the recent past purchase occasions.

$$PASTPR_{ijt}=EXP\sum_{m=1}^{5}\frac{\rho^{m-1}\ln(P_{ijt-m})}{\sum_{m=1}^{5}\rho^{m-1}}. \qquad 2.13$$

When $\rho = 0$, the PASTPR formulation reduces to P_{ijt-1}, similar to the situation in which $\lambda = 0$ in Lattin and Bucklin (1989).

Thus, Kalwani et al have a very rich formulation for the reference price. Like Winer (1986), rational expectations are assumed so that the parameters of the reference price model can be estimated by replacing RP_{ijt} by P_{ijt} (in equation 2.12) and using OLS regression. The parameter ρ is estimated to maximize R^2 (probably by a grid search procedure). The value of $\rho = 0.25$ is found to give a better fit than $\rho=0$. Interpreting the α level for this estimated PASTPR coefficient is difficult given the manner in which ρ is estimated. In terms of overall fit of the reference price regression, the adjusted R^2 is 0.2784. Kalwani et al interpret the coefficients in the model 2.12 as revelant of the effects of the independent variables on price expectations. Given that actual prices were regressed, these interpretations are not entirely justified. For example, the finding of a negative and significant FOP coefficient is interpreted to be suggestive that consumers exposed to frequent price promotions for a brand come to expect that brand to be always available at a

discounted price. A simpler explanation is that since actual prices were regressed, brands that were frequently promoted (i.e had high FOP) would necessarily also have lower prices over time.

In the choice model, both GAIN and LOSS are significant and correctly signed. The asymmetry in the coefficients is also supported with the GAIN coefficient smaller in magnitude than the LOSS coefficient. The elasticity for LOSS is also greater in magnitude than the elasticity for GAIN. Kalwani et al do not report the results of the choice model estimation for the assumption of $\rho=0$. The low value for adjusted R^2 is puzzling as it involves regressing the current period's prices on a weighted mean of past period's prices. It may be noted that only Kalwani et al's specification as a log mean of previous period's prices is consistent with the formulation of Helson's theory, which is cited as the rationale for the reference price model by all the empirical exercises.

Other Studies. Two other unpublished papers, Raman and Bass (1988) and Gurumurthy and Little (1988) also test for asymmetric effects of deviations from reference price. Raman and Bass (1988) test for this effect by modelling aggregate data with a switching regression model of market share.

$$MS_{jt}=\beta_0+\beta_1 RP_{jt}+\beta_2 ADV_{jt}+u_t, \; if \Delta_t > K. \qquad 2.14$$

$$MS_{jt}=\gamma_0+\gamma_1 RP_{jt}+\gamma_2 ADV_{jt}+v_t, \; if \Delta_t \leq K. \qquad 2.15$$

where $\Delta_t = P_t - RP_t$.

i.e the market share is affected by either of two regimes, depending on whether or not the observed price is greater than the reference price. It is not clear why RP_t rather than P_t is the independent variable in the regressions above. This pair of equations is estimated for each of five brands of an unnamed non-durable good. Like Winer (1986) therefore, all the independent variables are expressed in relative terms.

Rational expectations are again assumed for the reference price specification. The price series P_{jt} is analyzed by Box-Jenkins methods to arrive at the best specification. The random walk, $P_{jt} = P_{jt-1} + e_t$, where e_t is white noise gives the best fit. Hence, reference price is operationalized as P_{jt-1}. The threshold value K is positive for the best fitting model and the coefficient of RP_t is more negative in the first regime as compared to regime 2; this is interpreted as confirming the reference price model. Again, the nature of the estimation procedure makes it difficult to interpret these statistical tests. Overall though, the two regime model is shown to fit significantly better than a single equation model.

Gurumurthy and Little (1988) test for a three-segment price response function with a multinomial logit model. Their utility specification is

$$u_{ijt}=\alpha_j+\gamma_1 BL_{ijt}+\gamma_2 SL_{ijt}+\gamma_3 Z_{ijt}+\gamma_4 FOP_{ijt}+\gamma_5 RP_{ijt} \\ +\gamma_6 GAIN_{ijt}+\gamma_7 MID_{ijt}+\gamma_8 LOSS_{ijt}+\epsilon_{ijt}. \qquad 2.16$$

GAIN, LOSS and MID are defined as deviations of the actual price in a range around the reference price. Thus,

$MID_{ijt} = (P_{ijt}\text{-}RP_{ijt}) / (a/2)$,

if $RP_{ijt} - a/2 < P_{ijt} < RP + a/2$, 0 otherwise;

$GAIN_{ijt} = (RP_{ijt}\text{-}P_{ijt}) / (a/2)$,

if $P_{ijt} < RP_{ijt} - a/2$, 0 otherwise;

$LOSS_{ijt} = (P_{ijt}\text{-}RP_{ijt}) / (a/2)$,

if $P_{ijt} > RP_{ijt} - a/2$, 0 otherwise.

The variable a is defined as a latitude of acceptance,

$a_{ijt} = \partial S_{ijt}$, where, $S_{ijt}^2 = \gamma S_{ijt-1}^2 + (1-\gamma) (P_{ijt-1} - RP_{ijt-1})^2$.

i.e. the latitude of acceptance is set proportional to smoothed fluctuations of price around the reference price as measured by a standard deviation like quantity.

The parameter γ is estimated by grid search to maximize U^2, a measure of goodness of fit based on a comparison of the log likelihood of the estimated model and that of a "constants only" model. The model is estimated for different values of $\partial = 0,1,2$. Reference price is operationalized as in Lattin and Bucklin (1989) as an adaptive expectation,

$$RP_{ijt} = \beta_R RP_{ijt-1} + (1-\beta_R) P_{ijt-1}. \qquad 2.17$$

The model is estimated on two datasets for panels of coffee purchasers. As predicted, the price response is flat within the latitude of acceptance i.e. the

coefficient of MID is not significant. The LOSS coefficient is larger in magnitude than the GAIN coefficient in both panels.

The results seem supportive of the theory of a latitude of acceptance, within which price response is flat. A point of concern with the estimation is the use of grid search independently for estimating the best decay parameters in the brand loyalty and reference price specifications. Also, as in Raman and Bass (1988), reference price rather than actual price is used as an independent variable.

Thus, while all of the empirical work has common meeting points in specifying the reference price model in that, (1) reference price depends on past prices observed, (2) reference prices are held for each of the brands in the set of available alternatives, (3) the sensitivity of utility to price changes in the neighborhood of the reference price, and (4) all consumers are affected similarly by reference prices, the exercises vary in the operationalizations of the model.

Winer (1986), Kalwani et al (1990), and Raman and Bass (1988) invoke the rational expectations hypothesis, assuming that consumers' reference prices are unbiased estimates of the actual price, while Lattin and Bucklin (1989) and Gurumurthy and Little (1988) use an arbitrary deterministic adaptive expectations model, which assumes that consumers update their reference price based on the error in the previous period's forecast.

We discuss below some of the problems that are common to more than one of these exercises.

First, the use of forecasting models to operationalize reference price is problematic. Models of expectation like the adaptive, extrapolative and rational versions that have been used in these exercises come from an economic tradition of research on understanding how current choice depends on expectation of future happenings. For example, a farmer who has to decide on allocating farm land among different crops has to have some forecast of the prices of these crops at the end of the harvest. This process of observing past prices and trends therein and hence using these past prices to forecast future prices is markedly different from the psychological processes of perception and adaptation that motivate the theory of reference prices. Further, in the economics tradition, the market is assumed to clear in each season, so that at the end of the season, there is "real" information in past prices received as these are the outcomes of a demand-supply equilibrium. From a coffee purchaser's viewpoint, it is not very likely that she anticipates anything close to an equilibrium at each purchase occasion. If anything, in markets like the coffee market in which there is heavy promotion, she would probably expect a changing price scenario at each purchase occasion, and the price sensitive among the consumers would tend to take advantage of the disequilibrium.

A second concern has been that previously expressed by Jacobson and Obermiller (1990), who take issue with the rather strong assumption of rational expectations that some of these exercises make, and attempt to test the assumption in an experiment. Subjects were asked to predict the prices of five brands of tuna fish at a local supermarket for the next week by giving them prices for the previous

weeks. Jacobson and Obermiller discovered that both specifications--adaptive and rational expectations--lead to biased estimates. A serial correlations model was shown to have the best fit. Their test, however, of the adequacy of any of these various predictive approaches, is not sensitive to the hypothesized nature of the reference price effect as a moderator of the effect of current price on choice. Subjects in their experiment are not asked to make choices or indicate purchase intentions.

A third concern is the important assumption of all the reference price models reviewed that consumers track prices of all brands across purchase occasions. In a recent study by Sawyer and Dickson (1990), 50% of consumers could not recall the exact price of the brand they had purchased within thirty seconds of having placed the object in their shopping cart. In this study, fewer than 20% of consumers were observed to examine a brand other than the one that they purchased. If the figures in Sawyer and Dickson's study are any indication, it becomes difficult to accept the assumption of high price involvement implicit in the reference price research. Similarly, Krishna, Currim and Shoemaker (1991) report that a large proportion of consumers do not remember regular and sale prices of several brands of frequently purchased products.

Statistical concerns about the empirical exercises also exist. One does not expect reference price for a brand to change a lot over the period of purchases in a year, for then it ceases to retain its meaning as a standard for comparison. And if

the reference price does not change, the intercept (whose coefficient is α_j), P_{ijt} and RP_{ijt} become very collinear.

A fifth concern is the serious statistical problem of the simultaneity bias with Winer (1986) and Kalwani et al (1990). In both their studies, the reference price equation is estimated by OLS, and the forecasted reference price inserted in the brand choice model. In particular, the utility specification is

$$u_{ijt}=\alpha_j+\alpha_1 P_{ijt}+\alpha_2 (RP_{ijt}-P_{ijt}) + \ldots +\epsilon_{ijt}. \qquad 2.18$$

Since RP_{ijt} is estimated from the regression of P_{ijt} on the variables assumed to affect RP_{ijt}, in effect, the critical difference variable in the above equation becomes

$$RP_{ijt}-P_{ijt}=\mu_{ijt}-v_{ijt}. \qquad 2.19$$

(i.e the difference between two errors, the error in the specification of RP_{ijt} and those in using RP_{ijt} as a forecast of P_{ijt}). Individual differences not captured by the BL variables etc. could then be present in both ϵ_{ijt} and in the difference RP_{ijt} - P_{ijt}, causing the coefficient of this difference in the logit estimation to be biased. The findings of Raman and Bass(1988) are also subject to a similar bias. The other two exercises avoid this problem by choosing arbitrary deterministic specifications for RP_{ijt}. It is difficult to justify either of these approaches to specifying RP_{ijt}, and hence to interpret the significance of the "P-RP" coefficient as support for the proposed reference price theory.

Finally, another interesting commonality is the treatment of consumer heterogeneity in the four models of individual choice. All of them assume that the consideration set of brands is the same for all consumers for all purchase occasions, and that the price coefficients are the same for all brands and all consumers. Kalwani et al (1990), and Gurumurthy and Little (1988) control for individual differences in brand preferences by specifying brand loyalty variables. None of the models gives any emphasis to the last price actually paid by the consumer. If consumers are as price sensitive as these models assume, the last price actually paid should be at least as indicative of the future behavior of a consumer as the last brand purchased.

Thus, evidence for reference price effects on real purchase data in the literature is mixed. While there are recurrent findings such as a significant effect of deviation of actual price from the reference price, the operationalizations of the models raise several questions about the validity of the proposed source of these effects.

Price-based Market Structure

Market structuring refers to a grouping of the brands in the market such that brands within groups compete more with other brands in the group than with brands outside the group.

In innovative analyses of panel data, Grover and Srinivasan (1988) and Zenor (1989) demonstrated that if consumers are segmented on the basis of their stable

consideration sets, the different consideration sets corresponding to these segments will also define market structure with overlapping clusters of brands.

In this section, we review two recent articles that suggest that if consumers' price sensitivity is also taken into account along with brand preferences, the picture that emerges of the market is that of a structure of price tiers (i.e. brands within the same price range competing more with each other than with brands priced below and above this range). Both models suggest that it is this price tiered structure that results in the asymmetric nature of competition between national and private label brands. That is, when a national brand drops its price, it competes with and draws share from the private label brand. But when the private label brand cuts its price, it does not share from the national brand.

Blattberg and Wisniewski (1989) draw hypotheses for the aggregate response to price changes from a simple utility specification at the individual level. Consumer i's utility for brand j is specified as

$$u_{ijt}=\theta_i q_{ijt}-p_{ijt}, \qquad 2.20$$

where q_{ijt} is the perceived quality of brand j. Then, consumer i chooses brand j over brand k if,

$$u_{ij}-u_{ik}=\theta_i(q_{ijt}-q_{ikt})-(p_{ijt}-p_{ikt})>0; \qquad 2.21$$

equivalently, if

$$\theta_i(q_{ijt}-q_{ikt})>p_{ijt}-p_{ikt}. \qquad 2.22$$

$R_{ijkt} = \theta_i (q_{ijt} - q_{ikt})$ is defined as consumer's relative preference for brand j over brand k. Blattberg and Wisniewski show that if R_{ijk} is distributed as a U-shaped or J-shaped distribution (such as a Beta distribution), then there will be an asymmetry in the observed pattern of cross-price elasticities, with the cross-price elasticity of the lower quality brand with respect to the higher quality brand being greater than the cross-price elasticity of the higher quality brand with respect to the price of the lower quality brand.

Blattberg and Wisniewski (1989) further assume that national brands are perceived as higher in quality than private label brands, and that higher quality brands have higher regular prices. They test for the predicted pattern of cross-price elasticities by specifying overall sales, S_{jt} as

$$S_{jt}=\exp(\alpha_j-\beta_1 P_{jt}+\beta_2(\frac{P_{jt}-d_{jt}}{P_{jt}})-\sum_{j\neq k}\frac{\gamma_{jk}}{d_{kt}}+\theta_1 ADV_{jt}-\lambda_1 T_{jt}+\theta_2 W_{jt}+\alpha_3\phi_j) \quad 2.23$$

where

α_j is a constant for brand j that captures "attractiveness" of brand j that is separate from the other independent variables inlcuded,

P_{jt}, d_{jt} are regular and actual prices of brand j at time t,

ADV_{jt} = 1 if brand j is advertised at time t, 0 otherwise,

T_{jt} measures deal decay, thus,

T_{jt} = 0, during nondeal weeks,

= n-1, during the nth week of a multi-week deal,

W_{jt} is a variable that adjusts for whether the deal occurs during the first three days, or the next four days of the week, and

ϕ_j is a dummy variable that captures seasonality, set at 1 during Easter, Thanksgiving, and Christmas, and at 0 otherwise.

Data for four product categories--flour, margarine, bathroom tissue and tuna fish--are analyzed at the brand level for each of 28 brands for 48 weeks. High levels of fit are reported with adjusted R^2 in the range of 0.75 to 0.95, except for the generics.

The pattern of cross-price elasticities that emerges closely approximates the predictions. Price cuts in brands in higher price tiers affect other brands in their price tier and in the next lower tier. Price cuts in brands in lower price tiers do not affect brands in higher price tiers.

Blattberg and Wisniewski make a significant contribution by suggesting price as an attribute that determines the competitive structure of the product-market scenario rather than only affecting within segment competition in a brand-based structure. The close match between the aggregate predictions and the actual pattern of cross-price elasticities is provocative and calls for further testing of the phenomenon at the individual level. Finally, it reinforces the argument that there is information in the past prices actually paid by a consumer and suggest that consumer purchases over time tend to be restricted to a well-defined price range.

Kamakura and Russell (1990) arrive at similar conclusions as Blattberg and Wisniewski (1989) through a different empirical approach, but a very similar utility model. Consumer i's utility for brand j at purchase occasion t is specified as

$$u_{ijt}=\alpha_{ij}+\beta_j P_{ijt}+\epsilon_{ijt}. \qquad 2.24$$

The error ϵ_{ijt} is assumed to be distributed as i.i.d. Weibull, so that the parameters can be estimated by the multinomial logit model. Extending the work of Grover and Srinivasan (1987) and Zenor (1989), Kamakura and Russell segment consumers into clusters that are homogeneous in terms of both the brand-specific utilities and the price sensitivity parameter. "Loyal" segments of consumers who just purchase one brand are excluded from this analysis. The number of switching segments is chosen to minimize a variant of Akaike's information criterion.

The results of the analysis are remarkably similar to those of Blattberg and Wisniewski (1989). For the five switching segments, the pattern of purchase probabilities for the various brands indicates that brands tend to compete with other brands in their own price tier. Also, the segments seem to be located around various points in the price continuum in that their purchase probabilities are not spread equally over the four brands. Rather, they seem to be clustered around brands that are similarly priced. It may be noted that as a consequence of the estimation procedure, one of the loyal segments is a segment "loyal" to the private label brand. It would appear to be more valid to interpret this segment as highly price sensitive,

as the consumers in this segment seem to restrict their purchases to the cheapest brand.

Thus, Kamakura and Russell's research reinforces the notion that price could be a determinant of market structure.

Non-Compensatory Models of Price Effects

Another kind of severe effect of price on consumer choice is a non-compensatory effect (i.e. when the consumer eliminates brands based on price levels). If price is the first attribute on which eliminations are done, then this would indicate very high sensitivity to price.

Johnson and Meyer (1984) show that if a compensatory model is used to measure attribute weights when the actual choice process is non-compensatory, the "importance" of attributes used in the filtering or elimination process will increase as the number of choice alternatives increases. It is interesting to note that in their experiment involving apartment choice, the attribute that emerged as increasingly important, as the number of choice alternatives increased was price (i.e. rent). Olshavsky and Acito (1980) point out that if a compensatory model like the conjoint analysis model is used on the outcomes of an underlying non-compensatory process, the revealed part worths of the important attributes would be greater than the sum of part worths of all the lesser important attributes.

Recent efforts in the stochastic choice literature in marketing have attempted to develop variants of Tversky's Elimination By Aspects (1972) model for dimensional

variables such as price (Manrai and Sinha 1989; Rotondo 1986) and to study the effects of promotion (Fader and McAlister 1989). While the EBA model is not strictly speaking a non-compensatory model because of the probabilistic nature of the specification, these models approximate a situation in which price or promotional information is used as a basis for making eliminations.

Fader and McAlister (1989) propose and estimate a model at the individual level. The consumer is assumed to switch probabilistically between screening acceptable brands on the basis of promotion and choosing among all acceptable brands. Choice among brands in the consideration set is proposed to follow an attraction model:

$$PROB_{ijt}=\gamma_i \frac{\alpha_{ij}Z_{jt}}{\sum_m \alpha_{im}Z_{mt}} + (1-\gamma_i) \frac{\alpha_{ij}}{\sum_m \alpha_{im}} \qquad 2.25$$

if some acceptable brand is on promotion and

$$PROB_{ijt}=\frac{\alpha_{ik}}{\sum_m \alpha_{im}} \qquad 2.26$$

if no acceptable brand is on promotion.

The parameter γ_i stands for the probability that consumer i will restrict her choice to promoted acceptable brands given that some acceptable brand is on promotion. Fader and McAlister estimate the model (both the set of acceptable

brands and the parameters of the model) separately for each consumer in a panel. The model is shown to have comparable levels of fit to a multinomial logit model estimated at the individual level and much better fit than an aggregate multinomial logit model.

The stability of the individual level parameter estimates is sought to be established by a boot-strapping procedure that involves simulating samples and tracking the variability of parameter estimates across these samples. An issue of concern about the validity of such a procedure for this particular model is that all the parameters of the model are constrained to lie in the (0,1) range. Besides, the brand attractiveness parameters have to sum to one. The parameters being thus severely constrained, it might be appropriate to transform the estimates for normality before concluding that these paramater estimates are stable by the usual normal distribution based tests.

The median value estimated for γ_i, the promotion sensitivity parameter is 0.6, an indication that there is some tendency for consumers to screen acceptable brands on the basis of promotional status. Another interesting finding is that several panelists had brands in their consideration sets that were "marginally" acceptable i.e. preference parameters α_{ij} for these brands were extremely low and these brands had a reasonable probability of purchase only when they were the only brands in the acceptable set that were on promotion.

Manrai and Sinha (1989) describe and demonstrate the estimation of an elimination by aspects model which is the dimensional analogue of Tversky's (1972)

feature-based EBA. The model is estimated on data related to choice among business schools. Comparisons with the independent multinomial logit (IML) model are done at the overall prediction level and not at the individual attribute sensitivity level.

Rotondo (1986) also demonstrates a method of incorporating the effects of price in the EBA model. He does not offer an estimation procedure or an actual analysis of price effects. Various functions for scaling price effects are empirically compared on survey data and a linear measure is shown to fit best.

The models of both Rotondo (1986) and Manrai and Sinha (1989), at least as presented, are suitable for measuring price effects in a static setting, like data collected in a one-time survey, and are not vastly different from Tversky's suggested method for incorporating effects of dimensional attributes i.e. by framing them as nested sets of features.

A useful extension of this work would be to develop a model for dynamic settings, allowing for tracking effects of price as it changes across time. Such a model would be more directly to what appears to be accepted benchmark model, that of Guadagni and Little (1983).

The model of consumer price inertia proposed in the next chapter attempts to unify the concepts and findings of the research reviewed in this chapter. The notion of adaptation is shifted to the category level, individual differences are specified, the price-tiering phenomenon is specified at the individual level and possible noncompensatory effects of prices are specified.

CHAPTER 3
MODEL OF CONSUMER PRICE INERTIA

Patterns of Price Sensitivity Inherent in Model Specifications

Empirical research about brand choice in the modelling tradition in marketing and consumer behavior has usually followed one of two routes:

(1) structuring the alternatives in the market and/or consumers in the marketplace (e.g. Grover and Srinivasan 1987; Shugan 1987; Urban, Johnson and Hauser 1984; Zenor 1989)

(2) assuming a structure, and specifying a choice model with a particular mathematical form for the probability of choice (e.g. Guadagni and Little 1983; Lattin and Bucklin 1989; Winer 1986).

The objectives of both kinds of research are similar. They both attempt to understand the dynamics of the market in terms of the effects of short term promotions, price cuts, etc. Also, they attempt to understand the statics of the market in terms of the structure of competition amongst the brands in the product market and the structure of consumer preferences in terms of underlying brand loyalties, price sensitivities etc.

As with any modelling effort, or indeed, any empirical research, the knowledge or insight generated crucially depends on the underlying assumptions. In particular,

we discuss below, the assumptions of consumer homogeneity and the mathematical form assumed for the specification of choice probability.

The Treatment of Consumer Heterogeneity

Differences among consumers can be specified on several dimensions such as

(i) brand preferences,

(ii) sensitivity to price/promotion etc.,

(iii) consideration sets of brands,

(iv) nature of choice process (compensatory versus non-compensatory),

(v) products perceived as substitutes,

(vi) preference for variety,

(vii) brand loyalties (as distinct from brand preferences).

Each empirical effort accounts for some of these differences and assumes homogeneity on the other dimensions. However, consumers may differ on all these dimensions and more. Consequently, the choice in each study to focus on some differences and not on others in a large way affects the understanding generated from the estimated parameters of the model. Considerations of parsimony and statistical significance levels and the typically small number of purchase points for which data are available at the household level make this choice inevitable. All differences cannot be modelled.

A notable exception may be found in Fader and McAlister (1990) who estimated models of choice behavior at the household level, and allowed household

level differences on almost all the dimensions mentioned above. Consequently, a great deal of understanding about the statics and dynamics of the marketplace was generated. For example, the phenomenon, of "marginally acceptable" brands in consumer consideration sets (i.e. brands whose probabilities of purchase are near zero when not on promotion and which increase dramatically when they are on promotion) may not have been discovered were not consumers allowed to differ in both consideration sets and promotion sensitivities.

Usually though, the decision to include some differences and not others tends to cloud the understanding generated by the estimated parameters of the model. Consider the following examples.

Guadagni and Little (1983) specify only differences in brand loyalty amongst members of the panel. All members are assumed to share the same consideration set. If the actual underlying distribution of consideration sets across these consumers is disjoint (e.g. half the consumers choose among brands 1-4 and the other half choose among brands 5-8) and there is variation in prices of all the brands across time, then the price sensitivity parameter estimated from the model would be smaller than if estimated separately for the two different segments. Grover and Srinivasan (1987) and Zenor (1989) model market structure as it results from the differences in consideration sets across consumers. In both their schemes, variety-seeking consumers who frequently switch between two brands to satisfy this desire and price-sensitive consumers who also frequently switch between the same two brands to avail of temporary promotions would be classified in the same segment as their

consideration sets would be similar. But the resultant market structure which is expected to reflect the competitive situation among brands disguises the nature of the competition among these brands. A price change in one of these brands might affect the behavior of the price sensitive consumer very differently than it affects the variety-seeking consumer.

Thus, the understanding derived from an empirical investigation can often disguise the "true" underlying statics and dynamics of the product-market scenario. Of course, to claim that analysis of purchase data alone can completely reveal all aspects of the structure and the response tendencies of the consumer population would seem, with our current knowledge of methods of analyses and the current size of panel datasets, to be very ambitious. Our intention, in the model of consumer price inertia to be described in this chapter, is hence, not to attempt to uncover the truth hidden by previous research. Rather, it is to provide a "plausible rival hypothesis" that analyzes movements in the marketplace with special emphasis on price by allowing for considerable differences among consumers in price sensitivity, and to examine both support and contradictory evidence from the empirical and conceptual research reviewed in the previous chapter.

Mathematical Form

From the discussion in the previous chapter, we see that two fundamentally different kinds of models have been used to estimate the effects of price and promotion on individual choice:

(i) compensatory models like the multinomial logit model, and

(ii) probabilistic elimination models like the elimination-by-cutoffs model.

A property of the multinomial logit model is that brands with higher market shares automatically have lower associated price elasticities (Russell and Bolton 1987). Now, most empirical models are judged/evaluated on the basis of overall levels of fit compared to a base model which predicts that market shares are constant across time. Predictive validation is also employed where there are several data points available. Thus, models may have good overall fit with the data while not fitting each individual feature of the response like the "true" pattern of price sensitivities. For example, consider a brand that we "know" has a large market share only because of its low price. We would expect price elasticity for this brand to be high. A multinomial logit model fitted on a set of brands that includes this brand would bias the estimated price elasticity of this brand downwards.

Thus, the mathematical form assumed by a model can also cloud the understanding generated by a model about the patterns of price sensitivity prevalent in the marketplace.

A New Approach to Modelling Choice

The pioneering Guadagni and Little (1983) article sparked much interest in empirical research analyzing data from consumer panels in different ways. Perhaps because of the nature of the data available, much of this research has specified brand preferences and price sensitivities as important variables that determine both the

statics and dynamics of the marketplace. The traditional emphasis on branding and creating brand loyalties as strategies for long term profitability has surely had an effect on the way modellers specify market structures and probabilities of choice.

(1) Brands or brand-size combinations are always the units of analysis i.e. probabilities of choice and the structure of the marketplace are always specified in terms of brands or brand-sizes.

(2) Consideration sets are specified in terms of brands.

(3) Individual differences are often specified in terms of brand preferences and brand loyalties.

As argued in the introduction, it is our contention that the increasing competition among brands in many frequently purchased consumer product categories has the effect of diminishing perceived differences among brands. Price then becomes a salient and easy attribute on which alternatives in the marketplace can be discriminated.

Further, there is much research on the tendency of consumers to infer the relative quality of a brand from its relative price (Olson 1977; Monroe and Petroshius 1981). Other research on the nature of competition amongst brands has used the findings of the price quality research to justify the assumption of all brands being positioned at the same spot on the price/quality continuum. Thus, even if there are perceived differences among brands, the differences are often some function of the differences in prices. For example, a generic liquid dishwashing detergent that is packaged like and looks like the national branded detergent may be perceived to be

different from the national brand only in terms of a subjective "quality" evaluation. Thus, this difference may as well be measured by price differences if there is a perceived monotonic relationship between price and quality.

Further, the research reviewed in the second chapter about the existence of price tiers and price as a determinant of competition again suggests that price may be as important or central an attribute as the brand name to at least some consumers.

Finally, in some respects, brand loyalty and price sensitivity may be conceptualized as the "opposites" of each other, so that a person who is brand loyal in any sense of the term is by definition price insensitive, and a person who is price sensitive is brand insensitive by definition. The models of both Kamakura and Russell (1990) and Blattberg and Wisniewski (1990) treat overall preference as a linear combination of brand preference and price sensitivity, suggesting that both these lie on the same unipolar scale. Krishnamurthi and Raj (1991) empirically demonstrate the negative relationship between brand loyalty and price sensitivity. It may be argued that brand and price sensitivities are conceptually on the opposite ends of the same continuum, for consumers who are brand loyal, are, by definition, not sensitive to changes in the price of their and other brands. Then, a model that controlled for individual differences in price sensitivity would perform just as well as a model that controlled for individual differences in brand loyalty. An important advantage gained by such a substitution is that the unidimensionality of price might make for a specification with fewer parameters.

It may be recalled that our primary objective is to develop a better understanding of the static effects of price differences among brands and the dynamic effects of price-related promotions on aggregate consumer choice. The discussion thus far suggests that a useful departure from the traditional specifications may be to develop "price" parallels of constructs related to brands.

An especially appropriate area of previous research where this approach may be useful is the recent research on reference prices reviewed in the previous chapter. The fundamental notion of "adaptation" to a price level is not unlike theories of learning and usage induced preference that are invoked to motivate brand loyalty.

We hence next develop the model of consumer price inertia to address the concerns discussed.

The Model of Consumer Price Inertia

Let (p_{i1},p_{i2}) represent the range of acceptable prices in a product category for consumer i. Let A_{it} represent the set of all brands that are priced in this range at time t, that is,

$$A_{it}=\{j \mid p_{i1} \leq P_{ijt} \leq p_{i2}\}. \qquad 3.1$$

Also, let u_{ijt} be the utility of brand j for consumer i at time t. Let $f_i(.)$ be a positive and monotonically increasing function. The model of consumer price inertia proposes that, if $j \in A_{it}$, then,

$$PROB_{ijt} = \frac{f_i(u_{ijt})}{\sum_{k \in A_{it}} f_i(u_{ikt})}, \qquad 3.2$$

and, if $j \notin A_{it}$, then,

$$PROB_{ijt} = 0. \qquad 3.3$$

The model thus hypothesizes that consumers choose among brands available in an acceptable price range that is pre-defined for the product category and is consumer-specific. An "attraction" specification is used for the probability of choice among members of the consideration set. Individual differences are specified in terms of the price ranges which are allowed to vary in terms of both width and location on the price continuum. The variable u_{ijt} refers, as before, to individual i's utility for brand j at purchase occasion t. Different variables such as price and promotional status may be specified to account for u_{ijt}.

The model thus proposes that there is "inertia" on the part of the consumer in terms of the prices actually paid for purchases in a product category. For consumer i, for example, we would expect to find all prices ever paid to lie in this range (p_{i1},p_{i2}).

This emphasis on prices actually paid in the past is the most significant departure from previous models of reference prices reviewed in the last chapter. The reference price models have assumed a similar process of adaptation for "exposure"

to prices of all brands, giving no special emphasis to the prices actually paid. Further, these models do not allow for individual differences in price sensitivity.

Now, as noted in the previous chapter, descriptive behavioral research in the recent past (Dickson and Sawyer 1990; Krishna, Currim and Shoemaker 1991) suggests that both these assumptions, are, at the least, questionable. On average, recall of prices is not very accurate, even for the purchased brand a few seconds after purchase. Further, there is variance across consumers in the extent of recall. There are some consumers who recall the exact price accurately. There are others who have no recollection of the price. Several consumers report not checking prices of all brands. Thus, with all these errors in encoding price information for all brands, it is doubtful if consumers can learn to adapt to reference prices for all brands in the market.

The model of consumer price inertia only requires that consumers adapt to purchasing in a certain range of prices for the category, not for every brand in the market. The model also allows for the width of the acceptable price range to vary across consumers, a very simple way of specifying individual differences in price sensitivities. Allowing for a range of acceptable prices is also consistent with the finding in the descriptive research that price recall in a range around the actual price was fairly accurate for many consumers.

The model is also consistent with the notion of price tiers developed in the articles of Blattberg and Wisniewski (1990) and Kamakura and Russell (1990) reviewed earlier. If segments of consumers have overlapping acceptable ranges at

various points on the price continuum, then higher priced brands compete with lower priced brands when they adopt a temporary price cut, by entering the consideration sets of many more consumers. Lower priced brands however cannot gain a similar advantage against higher priced brands by cutting price temporarily. This asymmetric competition between price tiers (Blattberg and Wisniewski 1990) is thus modelled directly at the individual level by our specification.

The greatest advantage of the model of consumer price inertia is that it allows for a tremendous variety of possible aggregate responses to price promotions. Different brands could have different price sensitivities. The same brand could have different price sensitivites at different points on the price continuum. Thus, unlike the operationalizations of the independent multinomial logit model used in previous reference price models which constrain all brands to have the same price sensitivities, the current model allows the patterns of price sensitivities to be determined by the data.

We next analyze the consequences of different assumptions of distributions of ranges across consumers for the pattern of aggregate price sensitivity.

Special Cases of Model

For the purposes of this discussion, let u_{ijt} depend only on α_j, the brand attractiveness constant. Four special cases of the model that link the model to previous models are discussed below (see Figure 3.1).

Case 1. The Null Model ($p_{1i} = 0$, $p_{2i} = \infty$, $\forall$ i). This is equivalent to the null model of Guadagni and Little (1983). It proposes that everyone shares the same consideration set, which consists of all brands in the market, and that market share changes from period to period are purely stochastic.

Case 2. Distribution across adjacent price ranges. Blattberg and Wisniewski (1990) present examples of price tiers that are disjoint. For example, their study lists five "premium" brands of margarine that are priced between 59 cents and 89 cents a pound, two "moderate" brands that are priced between 49 and 53 cents a pound, and a generic alternative that is priced at 35 cents a pound. Similar categories are listed for flour, bathroom tissue and tuna. If there are consumers who are "loyal" to these categories of brands and always restrict their purchases to one of these three categories, then their behavior is appropriately modelled by specifying three possible ranges of (p_{i1},p_{i2}) that are adjacent on the price continuum. This case of the model implies that as long as brands change their prices within the range of brands in their tier (as is likely for most short term promotions), there will be no changes in the market shares of any of the brands. It is only when the price increases or decreases are so as for the new prices to fall in the range of the tier above or the tier below (when there is deep discounting) will there be changes in the market share. The distribution of consumers across the different price tiers will determine the changes in market share.

Thus, this case is comparable to specifying a null model for brands in each of the price tiers separately, and is a less restricted model than Case 1.

Case 3. The Reservation Price Model: $p_{i1} = 0 \; \forall \, i$. This case specifies that all consumers have a reservation price p_{i2} (i.e. a maximum price that they are willing to pay for brands in a product category). There is no minimum price though - all brands below the reservation price are considered. The reservation price varies across consumers and price sensitivities of brands depends both on this distribution and on the position of other brands on the price continuum.

An unlikely consequence of this model is that as the reservation price increases, the number of brands considered increases. Thus, the size of the consideration set is positively correlated with the reservation price - a structure imposed on the data by the model which is implausible, for the consumers most likely to have higher reservation prices would probably be price-insensitive, and hence likely to purchase from the top brands, not from all brands in the market cheaper than the top brand.

The model though offers a plausible rival hypothesis for the central proposition of the reference price literature reviewed earlier. It may be recalled that the central prediction was that there is a range of prices around which price sensitivity is low, and that price response is asymmetric outside this range - the response being steeper outside the higher end of this range than inside the lower end of this range. The reference price models propose that this is so for all consumers and hence for aggregate market share, and trace the source of this effect to perceptual effects of price exposure.

PRICE CONTINUUM:

CASE 1. The Null Model : $p_{1i} = 0, p_{2i} = \infty , \forall i$

Segment 1 :
Segment 2 :
Segment 3 :

CASE 2. Distribution across adjacent price ranges (Price tiers)

Segment 1 :
Segment 2 :
Segment 3 :

CASE 3. The Reservation Price Model : $p_{i1} = 0 \ \forall i$ (Reference price)

Segment 1 :
Segment 2 :
Segment 3 :

CASE 4. Overlapping price ranges over the whole price continuum

Segment 1 :
Segment 2 :
Segment 3 :
Segment 4 :

Figure 3.1 Special cases of model of consumer price inertia

Case 3 points the source of such a pattern of sensitivities to be the distribution of reservation prices across consumers. In particular, a positively skewed distribution of reservation prices would lead to such a pattern of sensitivities around the mode of this distribution of reservation prices. A proof of this proposition may be found in Appendix A.

This case of the model thus offers a choice-theoretic explanation for the empirical findings about asymmetry and flatness of price response behavior around reference prices.

Case 4. Overlapping price ranges over the whole price continuum. This is the most general case of the model where p_{i1} and p_{i2} are unrestricted. Price sensitivity of a brand then depends upon the position of a brand on the price continuum and the distribution of the width and positions of consumer price ranges around this point.

We illustrate the predicted market share changes for changes in price of a target brand with an example.

Let x_1,x_2,x_3 and x_4 be points on the price continuum that define price ranges. i.e the possible ranges are (x_1,x_2), (x_1,x_3), (x_1,x_4), (x_2,x_3), (x_2,x_4) and (x_3,x_4). Let the following table of joint distributions represent the distribution of consumers across these ranges.

Table 3.1 Joint distribution of consumers with varying acceptable price ranges.

		Upper Limit			
		x_1	x_2	x_3	x_4
Lower	x_1	-	q_{12}	q_{13}	q_{14}
Limit	x_2	-	-	q_{23}	q_{24}
	x_3	-	-	-	q_{34}

q_{rs} is the proportion of consumers whose acceptable price range is (x_r, x_s). Let α_k represent the relative attractiveness of brand k. Let θ_{rskt} be a dummy variable indicating the position of brand k on the price continuum at time t.

$\theta_{rskt} = 1$, if $x_r \leq p_{kt} \leq x_s$, at time t

$= 0$, otherwise,

where p_{kt} is the price of brand k at time t. Then the market share of brand k at time t, by the model of consumer price inertia is given by

$$MS_{kt} = \sum_{r=1}^{3} \sum_{s=r+1}^{4} \left(\frac{\beta_{rskt}\alpha_k}{\sum_m \beta_{rsmt}\alpha_m} \right) q_{rs}. \qquad 3.4$$

Thus, each price range that the brand falls in, defines the competition for the brand in the range - this set of brands may or may not vary across the different ranges depending on the positions of the other brands on the price continuum. In some ranges, brand k may be the only brand priced within the limits so that the brand enjoys 100% share among consumers whose limits fall within the range. This may characterise both generic brands that are priced much lower than most of the brands and of premium brands that may be priced far higher than most of the brands.

Other brands may be priced in the middle of the continuum and shifts in their prices will lead to the competition changing across time. Both Blattberg and

Wisniewski (1990) and Kamakura and Russell (1990) report that national brands draw share from private brands and generic alternatives when they are on "deal."

The explanation for this occurence by the model of price inertia is that a cut in the national brand's price enables it to enter the consideration set of several more consumers whose price ranges earlier included only private brands and generic alternatives.

Fader and McAlister's (1989) finding about "marginally acceptable" brands is also accommodated by this model. A brand with a high "attractiveness" parameter α_k may never enter the consideration sets of several consumers until it is on promotion, with an accompanying price cut which enables it to compete with lower priced brands and gain large increases in share.

It can thus be seen that the model of consumer inertia is extremely flexible in allowing for a wide variety of aggregate responses to changes in price. It allows for the pattern of sensitivities to depend entirely on individual differences in acceptable price ranges.

It may be noted that the behavioral foundations of the model are rooted in the notion of "adaptation". It is our contention that a price sensitive consumer perceives brands in terms of their prices. Constant exposure to deals leads him/her to get used to certain prices that become salient for the product category. Repeated purchases in a product category in a certain price range cause a consumer to "adapt" to the price range. The process by which this adaptation takes place is similar to the formation of brand loyalty as the consumer learns over time, the quality levels

associated with various points on the price continuum and adapts to on a level that is satisfactory in terms of the price quality trade-off. Small changes in price in range around these points are not noticed and market share shifts take place only when prices change enough that a brand moves from one cluster of brands at a certain point on the continuum to another cluster at a different point on the continuum.

Comparisons with Other Models

The model of consumer price inertia is closest in spirit to the reference price models reviewed in the second chapter. The major conceptual difference is that it emphasizes the value of the information in the prices actually paid, while the reference price models assume that prices of all brands are monitored. One indication of high price sensitivity according to our model is that the variance in the prices paid in the past in a product category should be low.

Finally, our model is close to Fader and McAlister's (1990) EBA model of consumer response to promotions and to other elimination models (Rotondo 1986) that suggest that the existence of individualized price cut-offs may be an important means by which price changes affect consumer choice. Fader and McAlister's model, as may be recalled, proposes that consumers choose probabilistically between screening to choose among promoted accceptable brands and choosing amongst all acceptable brands. The empirical version of the model of consumer price inertia presented in Chapter 5 later proposes that the probability of purchasing a brand increases when its price lies within the cutoffs considered acceptable by the consumer.

Thus, much research in the recent past analyzing the effects of short term price promotions in the marketplace is consistent with the model of consumer price inertia.

CHAPTER 4
EXPLORATORY SURVEY RESEARCH

Tha main objective of the survey was to examine whether there was prima facie evidence for the model of consumer price inertia. A central premise of the model is that consumers have ranges of acceptable prices that they restrict their purchases to, and that different consumers have ranges that differ both in terms of their position on the price continuum and in their width. The main statistics of interest were the percentage of consumers who reported acceptable upper and lower bounds on prices that were within the observed range of prices for different frequently purchased products, and the shapes of the distributions of the various ranges.

Method

The Bureau of Economic and Business Research (BEBR) at the University of Florida conducts a monthly telephone survey of a random sample of Florida residents to track trends in consumer sentiment. A series of questions about beliefs and behavior related to price ranges for different product categories were added to the March 1992 administration of the survey. These questions added to the survey were pre-tested and administered over the phone by trained interviewers of the

Bureau. Respondents were adult members of households who were chosen by a weighted random digit dialling method.

Respondents were asked, for each of six products, whether they had purchased the product in the last month, and then the following information was obtained from purchasers of the product:

(1) the brand and quantity purchased, and price paid the last time that the product was purchased,

(2) certainty of brand and price recall, among those who recalled,

(3) the highest price ever paid for a particular size of the product,

(4) the highest price that the respondent would be willing to pay for the particular size of the product, and,

(5) the lowest price for the particular size of the product, below which the respondent would have concerns about the quality of the product.

The last two questions were used to derive the distribution of acceptable upper and lower bounds among the respondents. The question on the highest price ever paid helped establish the range of prices for the product category. At the end, all respondents were asked if they were the main food shoppers for the household, and the supermarket at which they made the majority of their purchases. Demographic information for the respondent and the household is routinely collected at the end of the BEBR survey, and was thus also available. A copy of the questionnaire is attached in Appendix B.

The questions were repeated, in the same order, for ground coffee, paper towels, beer, yogurt, dishwashing detergent, and men's dress shirts. For the questions about acceptable price bounds, the quantities of these products were fixed at a pound of coffee, a roll of paper towels, a six-pack of 12 ounce cans of beer, an 8 ounce container of yogurt, and one men's dress shirt. For dishwashing detergent, the pre-test revealed that respondents did not encode the sizes of their purchases in ounces. Hence, the acceptable price bounds were ascertained for one of small, medium, large, extra large sizes, depending on the size that they reported as having purchased last.

The rationale for including each of these products was as follows. Coffee was chosen, as it is the product category most frequently analyzed by previous research on reference prices. Dishwashing detergent and yogurt were chosen, as panel data on actual purchase behavior was also available (though for a different sample), allowing for a comparison between the actual and reported acceptable upper and lower bounds for prices. Paper towels and beer were chosen, as these were product categories in which there was a known spread of brands on the price-quality continuum, and both products are also frequently promoted. The category of men's dress shirts was chosen, as a contrast to the frequently purchased supermarket product categories, to estimate the extent to which the phenomenon was prevalent for a semi-durable product, for which the expected use of price-quality inferences and hence the a priori likelihood of consumers reporting upper and lower bounds would be high. A main point of departure from previous descriptive studies of price-related behavior (Dickson and Sawyer 1990; Krishna, Currim and Shoemaker 1991; Krishna

1991) was that questions were asked at the product category level, rather than at the brand level. Another point of departure from these studies was that the sample was randomly chosen and was from across the state of Florida. While this is a significant strength of the study, it also made it impossible to verify the accuracy of the prices of the brand purchases recalled. Five hundred and fifteen Florida residents were interviewed.

Results

Proportion of Purchasers and Recall of Last Purchase

Respondents were asked if they had purchased each of the six products in the previous month. The proportion of purchasers varied from 16% for men's dress shirts to 75% for paper towels (see Table 4.1). Subsequent questions were only asked of respondents who had made a purchase in the previous month. Respondents were then asked to recall the brand and quantity purchased, and the price paid the last time that the product was purchased. Reported recall levels for brand names were uniformly higher than those for price paid, except for dress shirts, for which price recall was as high as 98%, compared to just 56% for the brand name. The only other category for which the recall levels for brand name and price were close was paper towels, for which 80% remembered the brand name, and 74% remembered the price paid. It is also interesting to note that more respondents remembered the quantity of paper towels purchased (96%) than the brand name or price. Respondents who recalled the brand or price were asked how certain they were

about their recall. On a four point scale ranging from "Very certain" (scored as 4) to "Not at all certain" (scored as 1), the brand recall certainty mean scores were uniformly high, ranging from 3.69 for dress shirts, to 3.90 for yogurt. These scores were also uniformly higher than the scores for price recall certainty, which ranged from 3.37 for coffee to 3.57 for yogurt. It may be noted that there was no verification of the brand or quantity purchased or of the price actually paid by the respondent. Thus, the accuracy of the recall could not be tested. These data mainly reflect the relative salience of these cues (brand versus price) to the respondents. It appears that for all the supermarket categories, the brand cue was more salient than the price. For men's dress shirts, the price was more salient than the brand name for the majority of the respondents. Almost all respondents though remembered the store in which they had purchased their last shirt, indicating that perhaps the store name was more salient than the brand name. The percentages of respondents who recalled a price, but not the brand, for their last purchase, were an appreciable proportion only for paper towels (over 10%) and men's dress shirts (43%).

Upper and Lower Bounds

Respondents were asked to state the maximum price that they would be willing to pay for a particular size of the product. They were also asked if there was a price (for the same size of the product) so low that they would be concerned about the quality of the product. These questions directly address the central assumption of the model of consumer price inertia that consumers have these ranges of

acceptable prices to which they restrict their purchases. The prices that respondents stated as upper and lower bounds were adjusted to only capture bounds within the normal range of prices encountered for these product categories. For example, an upper bound of $50 for a pound of coffee is really not a meaningful upper bound, as the normal supermarket coffee brands are priced much below that level. Such a response was hence recoded to reflect the respondent's not possessing a meaningful upper bound. The cutoffs were determined by using the largest price cited by respondents to the question about the highest price paid in the past for a purchase in the category. The largest upper bounds allowed were $9.00 for coffee, $2.50 for paper towels, $6.66 for dishwashing detergent, $3.00 for yogurt, $9.00 for beer, and $100.00 for shirts.

Table 4.2 lists the proportions of respondents who reported upper and lower bounds, after these adjustments. The proportion of respondents reporting upper bounds was much higher than those reporting lower bounds. No respondent reported having only a lower bound for any of the six categories. The proportion of consumers having upper bounds (or reservation prices) only was between 30% and 40% for the supermarket items, but 0% for dress shirts. Among the supermarket items, beer had the largest reported proportion of respondents having lower bounds (42%) suggesting that price-quality perceptions were perhaps strongest for this category. The proportion of consumers who reported either an upper or lower bound ranged from 52% for coffee to 77% for beer. Thus, the findings represent prima facie evidence for the central assumption of the model, for a majority of consumers.

Distribution of Upper Bounds

The various cases of the model of consumer price inertia differ in the distribution of the upper and lower bounds of consumers across the price continuum. The proportion of consumers reporting upper bounds was much higher than those reporting lower bounds. Figures 4.1-4.6 depict the distribution of these upper bounds across respondents.

Coffee. The modal response for the reservation price for coffee was $2.00. Eighteen percent of respondents mentioned this amount as the maximum amount that they would consider paying for a pound of coffee. Sixty-eight percent of respondents had reservation prices that were at or below $2.00. If the majority of coffee brands are priced below $2.00, then, by the analysis described in the previous chapter, we would expect the reference price effect of the loss in share for a price increase being greater than the gain for a corresponding price cut. Thus, the distribution of upper bounds for coffee points to the model of consumer inertia as an alternate explanation for the findings of the asymmetic effects of price increases and decreases on market shares.

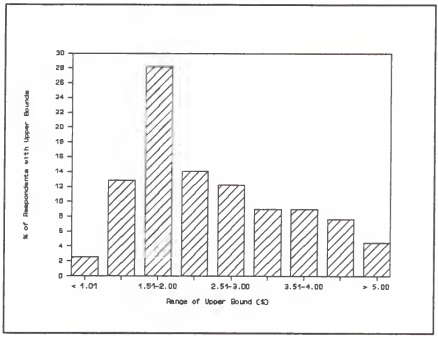

Figure 4.1 Distribution of upper bounds for coffee

Beer. The modal reservation price for beer was $4.00. Around 30% of respondents had upper bounds in the range of $3.75 to $4.25. The distribution also indicated that there were smaller segments of respondents with reservation prices less than and greater than $4.00. Around 12% each of respondents had reservation prices of $3.00 and $5.00. The overall distribution of reservation prices was fairly symmetric about $3.75. If the majority of brands are priced below $3.75, the asymmetric effect of gains and losses predicted by the reference price research might be expected. Else, if the majority of brands are priced above $3.75, then the opposite effect might be expected, with the response to price cuts steeper than the response to price increases.

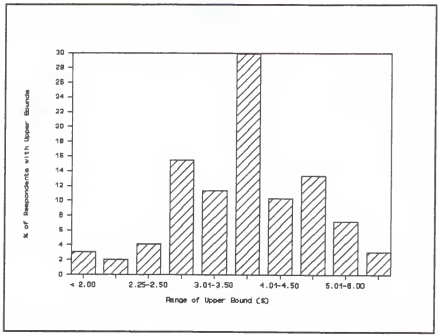

Figure 4.2 Distribution of upper bounds for beer

Paper Towels. The distribution of upper bounds for paper towels was particularly interesting in that a high proportion of respondents mentioned odd prices (prices ending in 9) as their reservation prices. Around 47% of respondents mentioned odd prices ranging from 49 cents to $2.09. This peculiarity in the distribution illustrates the process invoked by the model of consumer price inertia to explain the impact of short term price promotions on brand choice, and the choice-theoretic explanation for the asymmetry of the effects of price cuts and increases. The high proportion of consumers indicating their reservation prices as odd-ending prices suggests that for this frequently promoted category, consumers have adapted to these frequently advertised prices, to such an extent that they have coded their

maximum acceptable price precisely in terms of these advertised prices. For this category, it may also be remembered that the proportion of respondents recalling the brand (80%) last purchased was close to the proportion of respondents remembering the price last paid (74%). Also, the histogram in Figure 4.3 also indicates that the density function for the distribution of reservation prices is upward sloping for the most part, and indication that the asymmetry of responses to gains and losses predicted by reference price theory would hold for this category.

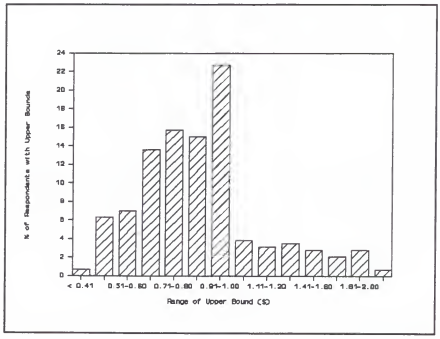

Figure 4.3 Distribution of upper bounds for paper towels

Dishwashing Detergent For detergents, since pre-tests revealed that respondents did not encode sizes very precisely in terms of the number of ounces, respondents were asked to recall the quantity last purchased as one of "small",

"medium", "large" and "extra large." It was expected that these designations would loosely correspond to 12 ounces, 22 or 32 ounces, 48 ounces, and 64 ounces, respectively. The subsequent questions about reservation prices and lower bounds were then asked for the same size as the respondent had last purchased. The most popular size was medium, which was the preferred size for over 50% of respondents. The distribution of reservation prices pictured in Figure 4.4 prices is for this segment that last purchased a medium sized container of dishwashing detergent. The most popular range of reservation prices was $1.26-$1.50; more than 27% of respondents had upper bounds in this range. A smaller segment of around 19% had upper bounds in the higher range of $1.76-$2.00, and an even smaller segment of 13% had reservation prices in the lower range of 91 cents to a dollar.

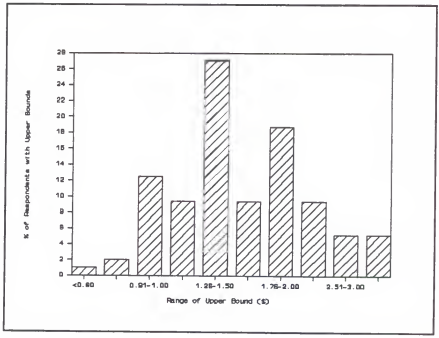

Figure 4.4 Distribution of upper bounds for medium sized detergent

The distribution of upper bounds was rather uneven across the price continuum, making it difficult to predict whether the reference price predictions would hold for this category.

Yogurt. Over 40% of respondents who expressed reservation prices for yogurt mentioned prices between 60 and 80 cents. Compared to the previous categories, the distribution of reservation prices across adjacent price tiers was more even, with small segments distributed all along the continuum. Thus, it was not clear whether the predictions of reference price theory would hold for this category. Close to a third of respondents mentioned an odd numbered reservation price ranging from 59 cents to $1.19, again suggesting some adaptation to regular exposure to these prices.

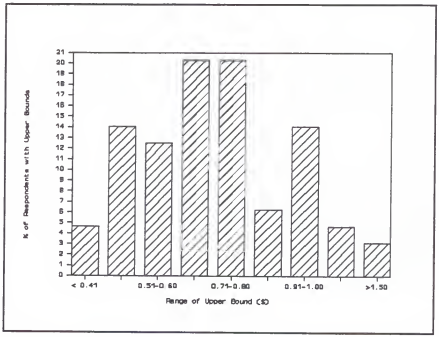

Figure 4.5 Distribution of upper bounds for yogurt

Men's Dress Shirts. Over a fifth of the respondents said that they would not purchase a shirt priced over twenty dollars. The distribution of upper bounds was sharply skewed negatively with over 70% mentioning bounds greater than twenty dollars. This suggests that for this category, responses to price increases may be less steep than responses to price decreases.

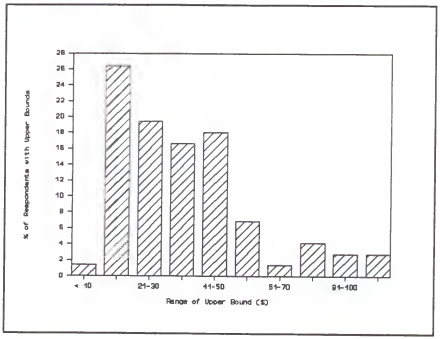

Figure 4.6 Distribution of upper bounds for dress shirts

Comparison of Survey and Panel Estimates of Distributions of Reservation Prices

Purchase data for yogurt and dishwashing detergent were also available. These data are described in the next chapter. For these categories, it is possible to compare the "actual" upper bounds, in terms of the maximum prices actually paid by consumers with the stated reservation prices by respondents in the survey, though

there may be some differences due to the differing time periods and the different samples for the two kinds of datasets. Figure 4.7 compares cumulative distributions of upper bounds for dishwashing detergent from three different sources, the highest price reported paid in the survey, the reservation price or the highest price that respondents said that they would be willing to pay, and the highest price actually paid by members of the panel.

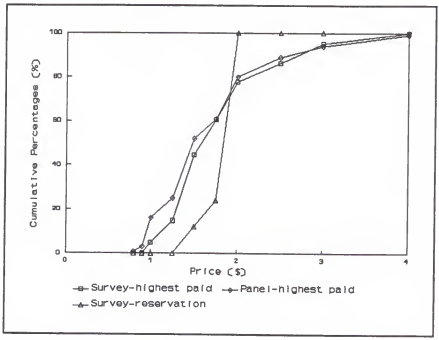

Figure 4.7 Cumulative distributions of reservation prices estimated from different sources for medium sized dishwashing detergent

It is interesting to note that the cumulative distributions of the reported highest prices paid and those actually paid are very similar, providing further prima facie evidence for the model's hypothesis that consumers's recall of actual prices paid may be quite accurate. The distribution of stated reservation prices though was markedly different. For example, twenty percent of consumers had actually paid

prices higher than $2.00, though no respondents reported willingness to pay more than this amount.

Figure 4.8 displays a similar comparison for eight ounce containers of yogurt. Again, the cumulative distributions of the highest prices reprotedly paid, and those actually paid were extremely similar. The distribution of stated reservation prices was however different, with an extremely negligible proportion of consumers expressing reservation prices over a dollar, while close to 20% of consumers had actually paid prices over a dollar.

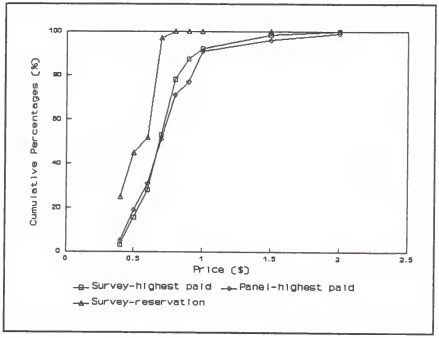

Figure 4.8 Cumulative distributions of reservation prices estimated from different sources for 8 ounce containers of yogurt

Discussion

The model of consumer price inertia is based on the notion that consumers have a range of acceptable prices for different product categories, and that these ranges vary in size and position on the price continuum. The main purpose of the survey was to assess empirically if this assumption had face validity. If the majority of consumers had reported upper bounds that were so large, or lower bounds that were so low, that these bounds would not be effective in eliminating brands from the consideration set, then the survey findings would have contradicted the assumptions of the model. The primary finding of the survey that supports the assumptions of the model is that a majority of respondents (ranging from 52% for coffee to 77% for beer) reported having upper bounds that were within the range of observed prices. The survey also confirmed that the lower bound was not a factor in limiting consideration sets, at least for the frequently purchased supermarket items. It was only for men's dress shirts that over 50% of respondents reported having lower bounds.

An intriguing, unexpected, and perhaps debatable, source of support for the model's hypothesis about the way in which prices affect brand choice was found in the specific prices stated as reservation prices for paper towels and yogurt. The model proposes that consistent exposure to advertised prices for frequently purchased products, and repeated purchase at these advertised prices, causes adaptation to these prices for the entire product category. Forty-seven percent of paper towel purchasers and 33% of yogurt purchasers mentioned odd prices as their reservation

prices, without being prompted with any price, indicating that these consumers had "learned" these prices for the product category. The finding that a large proportion of consumers for these categories encoded prices for the category at such specific advertised levels seems to indicate some support for the model's process theory of the operation of price effects on brand choice.

The idea that consumers have upper bounds or reservation prices for different categories is an established one, and not intended as the main contribution of this thesis. The intended contribution rather is on understanding how these reservation prices may form not only on the basis of a perceived price-quality relationship, but also from adaptation to lower price levels as a result of frequent exposure to promotional pricing. In this light, it was heartening to note the large proportion of respondents who reported reservation prices that were within the range of prices observed in these categories.

Prior to the survey, it was not entirely clear if consumers would also have lower bounds for these relatively inexpensive and relatively homogeneous product categories, especially at the product category level. For example, it may be argued that certain brands would be so familiar to consumers that however low the brand was priced, it would still be considered by the consumer. The pre-tests did reveal some confusion on the part of the respondents, who would sometimes ask if the question pertained to a single brand or to the entire product category. While in the main survey it was attempted to make clear that the question was to be answered "for any and all brands," it is difficult to be sure that all respondents understood and

responded to this question correctly. If they did, the survey found that the prevalence of lower bounds for the supermarket items was much lower than that of upper bounds. It was only for shirts that the proportion of consumers reporting lower bounds was over 50%.

It may also be argued that a telephone survey is not the best method of ascertaining the "true" upper and lower acceptable prices, and indeed, whether consumers have any bounds at all while actually making purchases, as respondents may "construct" ranges for the purposes of the interview. A counter to this thesis that the survey overstates the incidence of these acceptable price tiers is that these respondents did not have the benefit of being cued by a display and a range of prices to help remember prices paid, or bounds maintained. These bounds may be held unconsciously, or operate unobtrusively. For example, a consumer may always purchase the cheapest brand on the shelf, without ever having to remember the prices that she paid. An analysis of the prices she paid over time would however stongly reveal the operation of price as an upper bound, if brands across the product category were always priced at the same few price points (e.g. at a regular and "deal" price, which were the same or very close for several brands).

It is also interesting to compare the price recall levels in this study with those observed in previous studies, in which questions were asked at the brand level (Dickson and Sawyer 1990, Krishna, Currim and Shoemaker 1991). Dickson and Sawyer's study was conducted in situ immediately after a purchase, and around 20% of respondents could not recall the price. For beer, towels and yogurt, the

proportion was similar, even though in this survey, the respondent was far removed from the purchase. The main purpose for the last purchase recall questions was to ascertain the relative salience of these three attributes of a purchase: brand, size and price. For products such as beer and yogurt for which the brand name is part of the packaging, and hence accessible and impactful even after the purchase, (for example, each time, the refrigerator door is opened, an impression of the brand may be made) and recall may not be a very good measure of salience at the time of purchase. Reaction times to recalling or recognizing brands and prices may make for better measures of relative salience. It was only for dress shirts that price appeared to more salient than the brand name with 43% of respondents recalling the price but not the brand.

Thus, the survey findings do support the face validity of the model's assumptions. They establish that a significant proportion of consumers report at least an upper bound. I argue that these upper bounds are influenced by actual advertised prices that are frequently encountered. These bounds vary across consumers, pointing to a useful basis for segmenting consumers and also an alternate route to the asymmetric responses of the market to price cuts and increases of the same magnitude. Finally, the distribution of bounds suggests that the reference price hypothesis may be violated for some categories.

Table 4.1 Last purchase recall

Product	% buyers	Brand Recall (%)	Brand Recall Certainty	Quantity Recall (%)	Price Recall (%)	Price Recall Certainty
Coffee	46	97	3.85	91	61	3.37
Beer	26	99	3.89	99	76	3.42
Towels	75	80	3.74	96	74	3.49
Detergent	52	97	3.85	96	62	3.48
Yogurt	19	99	3.90	95	74	3.57
Dress Shirt	16	56	3.69	99	98	3.54

Table 4.2 Upper and Lower Bounds (%)

Product	% buyers	Upper Bound Only	Lower Bound Only	Upper and Lower Bounds	Neither Upper nor Lower Bound
Coffee	46	36	0	16	48
Beer	26	35	0	42	23
Towels	75	39	0	35	26
Detergent	52	34	0	35	31
Yogurt	19	34	0	31	35
Dress Shirt	16	0	0	58	42

CHAPTER 5
MODEL ESTIMATION

The model of consumer price inertia makes specific predictions about the process by which price and price changes affect brand choice. It hypothesizes that consumers learn ranges of acceptable prices for the product category, and restrict choice to these brands. The range of acceptable prices thus determines the consideration set, and brands enter and exit this set as their prices change from one purchase occasion to the next. This proposed effect of price is very different from the involved process suggested by reference price theory, which assumes that consumers learn reference prices for every brand, and react to deviations of the actual price of each brand from its reference price. Consumers are also assumed to choose among all brands in the marketplace, with an increase in choice probability for those brands for which the price is below the reference price. These alternative price effects were pitted against each other in a series of nested tests for three product categories. The next section describes the general strategy used to analyze the datasets. The succeeding section provides an overview of the three datasets analyzed. This is followed by a description of the exploratory data analyses on three datasets. The final section presents the analysis of the aggregated datasets for all three categories.

Model Testing Strategy

Datasets were analyzed for three product categories to allow for the testing of the alternative measures of price effects in different market conditions. The analysis was conducted in two stages. In the initial exploratory stage, the data were separated into homogeneous subgroups, and a nested series of models was tested for each of the subgroups. The objectives of this first phase were to detect circumstances under which the alternative specifications performed well in terms of goodness of fit, and also to uncover systematic sources of bias or error in the estimation due to problems specific to the datasets analyzed. In the interests of maintaining reasonable sample sizes for the analysis of these small subgroups, there were no holdout samples of households or purchases for the exploratory stage. In the second stage, data were combined across these subgroups and the data-related problems encountered during the exploratory stage were resolved. The models were re-estimated for these combined datasets for each of the three categories, and a new nested series of tests conducted with additional, refined measures of the variables of interest. The final analysis consisted of splitting the sample into estimation and prediction periods, and performing tests of predictive validation for the constructs of greatest interest.

Overview of Datasets

Data were analyzed separately for catsup, yogurt and dishwashing (or light duty) detergent. Household level panel data and store level causal data for both catsup and yogurt were obtained from A.C. Nielsen Company under the aegis of the

Marketing Science Institute's (MSI) Library of Single Source Data. Panel and store level data for dishwashing detergent were obtained from SAMI/Burke Incorporated. The data analyzed and the data cleaning procedures used for each of the segments for each of the three product categories are described in this section.

Catsup. Data for 93 Universal Product Codes (UPC) of catsup were available for a three year period (September 1985 through September 1988). The data spanned 2500 households who shopped in thirty-six stores in two cities, Sioux Falls, South Dakota and Springfield, Missouri, which were selected by A.C. Nielsen since they are demographically similar to the United States population as a whole. Store causal data (daily data on prices and promotional status of the various brands) were available in a "processed" form, after checks to maintain consistency in prices and promotional status across purchases by different households in the same store and week, for the UPCs with the largest shares. The procedures used to "clean" the data in this fashion are detailed in the documentation provided by A.C. Nielsen Company (1991). Analysis was restricted to households that made ten or more purchases, so as to have enough data for initialization, estimation, and prediction periods. Analysis was also restricted to households that purchased only among these large share brands. Analysis was also restricted to households that made more than ten purchases. The twelve brand-size combinations that constituted the market for the analysis were Heinz (14, 28, 32, 40, 44, and 64 oz), DelMonte (28 and 32 oz), Hunt's (32 and 44 oz) and a store brand (28 and 32 oz). The shares of these brand-size combinations in the two markets are listed in Appendix C.

Yogurt. Data for 412 UPCs of yogurt were available from A.C.Nielsen Company, the same source from which data for catsup were obtained. Different flavors of the same brand of yogurt were grouped together to define brand-size combinations for this analysis. Data were analyzed for the top share earning brand-size combinations in the two markets. These brands and their shares are listed in the Appendix D. As for catsup, store causal data for these brand-size combinations were available in a "processed" form, after running programs to remove inconsistencies in the data. Data were analyzed for households that purchased only one brand at each purchase occasion (purchases of multiple flavors of the same brand were included). As for catsup, analysis was restricted to households that made more than ten purchases.

Dishwashing detergent. Data for dishwashing detergent were obtained from SAMI/Burke Incorporated. Data were available for a panel of 2500 households for a two year period beginning April 1985. Store causal data were only available for the first year of this period, and hence analysis was restricted to this time period. As there were fewer observations, the initialization period was shortened to five purchase occasions, and analysis was restricted to households that had made more than eight purchases. As for the other categories, analysis was restricted to the top market share brand-size combinations. Twenty-nine brands were retained in the analysis. These brands and their shares are listed in Appendix E.

Exploratory Data Analysis

As mentioned earlier, the data were divided into homogeneous subgroups in the exploratory stage. Two bases were separately used to classify the households in the datasets. The first basis of segmentation was the combination of sizes that the household purchased over the period for which the data were available. This was because considerable size loyalty was expected for relatively "uninteresting" reasons such as household size, or possession of an automatic dishwasher (for the dishwashing detergent dataset). It was also desired to avoid confounding brand switching effects with size switching effects (which may be driven by considerations other than the process of adaptation driving the model of price inertia). For these reasons, the datasets were separated into groups that each purchased among the same size categories.

An alternative basis of segmentation that was used to "homogenize" the samples of households analyzed was the number of different brands purchased during an initialization period. It was expected that these segments would be behaviorally different from each other, especially in the manner in which they reacted to price changes. It was expected that households that switched often among brands, and hence had purchased a larger number of different brands in the initialization period would be more prone to adaptation to price levels, than households that purchased the same one or two brands repeatedly in the initialization period who would presumably be more brand loyal. Hence, support for the price tier specification was

expected to be higher among the segments with the smaller number of different brand purchases in the initialization period.

These bases of splitting the dataset into subgroups resulted in nineteen size-based subgroups and three "number of brands" subgroups for catsup. The single size loyal subgroups were not very large for catsup; only one subgroup that restricted purchases to the 32 oz size had enough observations to enable estimation of the models. There were three subgroups that restricted purchases to two adjacent size categories. The characteristics of these subgroups are summarized in Table 5.2.

A peculiarity of the yogurt market for the two cities that were studied was that in one of the two markets, the brand with the largest share was an eight ounce store brand which was available only in three stores that belonged to a particular chain. Since causal data for this market did not include information on the price or promotional status of all the other store brands, analysis for yogurt was done separately for the two markets for the segment that purchased any 8 ounce size container, and for this market, analysis was restricted to the stores in the chain. A majority of panel members were size loyal, purchasing either only 6 ounce or 8 ounce sizes throughout the period of panel membership. Accordingly, three segments of "medium/heavy" purchasers of yogurt (ten or more purchases over the three-year period) one segment defined across the two markets that purchased only 6 ounce containers, and two segments loyal to eight ounce sized containers in the two markets, were analyzed separately. The segmentation by the number of brands that were purchased in the initialization period (of the first six purchases) resulted in two

segments of consumers for each market, one that purchased just one or two brands, which may be interpreted as a relatively "brand loyal" segment, and the other that purchased three or more brands. Table 5.25 summarizes the number of observations available for estimation for each of these segments and the number of brands in each analysis.

The segmentation by the number of different sizes purchased over the period for which data were analyzed for dishwashing detergent resulted in six groups of panel members that made enough purchases to enable estimation of multinomial logit models. The segmentation by the number of different brand-sizes purchased in the initalization period led to three segments being retained for the estimation of the nested sequence of models. The characteristics of these nine segments are described in Table 5.33.

Measures

Price and promotion measures. Price was measured in unit terms[1] (in dollars per ounce). Promotion was coded as a dummy variable, taking value one if there was a special display in the store or a feature advertisement for the brand, and zero otherwise. It may be noted, that following the lead of the previous research in price

[1]Price expressed as full price rather than as price per ounce was also estimated for yogurt, for the aggregated dataset. The likelihood ratio statistic did not improve by much and the z-statistics did not change by much for one of the two yogurt markets for this alternate treatment of price. The likelihood ratio statistic was smaller for the other market for the full price variable version of the models' measures.

effects that used logit models (e.g. Guadagni and Little 1983), choice alternatives were specified as brand-size combinations. Thus, promotion was coded at the level of brand-size combinations. To avoid confusing the choice alternatives with the individual brands, as more than one alternative may correspond to the same brand, these brand-size combinations are henceforth referred to as items.

Price-based and item-based consideration set measures. These measures were constructed as dummy variables that indicated whether or not an item was in the consideration set as predicted by a price inertia model versus an item inertia model. The construct of inertia refers to the tendency to restrict purchases in a category to alternatives at the same level of an attribute (brand name, price range, size, brand-size, etc.). Thus, item (or brand-size) inertia may be measured as the coefficient of a variable (in a utility specification) that tracks the tendency to restrict purchases to a small set of items. If a few items are selected repeatedly, the item inertia measure would be expected to be a significant predictor of choice, and hence, the probability of purchasing an item should increase were the item to have been purchased in the recent past. Similarly, a price inertia measure can be constructed as the coefficient of a variable that tracks the tendency to restrict purchases to the same price range over time. The prices paid by a consumer in the past should indicate his or her likelihood of paying a certain price for a current choice. The probability of purchasing an item should increase if its price lies in the range of prices recently paid by the consumer. Behavioral measures of consideration set membership based on items or prices were defined. A special property of the multinomial logit model is

that for dummy variables, extremely large estimated coefficients approximate phased decision making behavior (i.e. large coefficients suggest that the dummy variable may act as the basis of cut-offs, or as the basis for elimination of alternatives from choice consideration). A proof of this property may be found in Appendix F. Smaller estimated coefficients that are statistically significant indicate support for a tendency toward phased decision making, or perhaps population heterogeneity.

Three different time periods were used to determine the appropriate consideration sets for both definitions of price and item based inertia:

1) The data was split into initialization and estimation periods. The initialization period consisted of the first five (for dishwashing detergent) or six (for yogurt and catsup) purchases and the estimation period of all the subsequent purchases. The items purchased at least once in the initalization period constituted the item-based consideration set for this operationalization. A dummy variable IT was defined to measure item-based consideration set membership. This variable was one for items that belonged to the set purchased in the initialization period, and zero for other items. Similarly, the range of prices (the maximum and minimum price) paid in the initialization period defined the acceptable range of prices for each household. A dummy variable TR measured membership in the price-based consideration set. If an item's price belonged to the range of prices paid in the initialization period, then TR took a value of 1. Otherwise, TR was set equal to zero.

It may be noted that the item-based consideration set is static, while the price-based consideration set is potentially dynamic for this definition of the two variables.

Items may enter and exit the consideration set contingent on their prices for each purchase occasion being within the consumer's upper and lower bounds.

2) Nonstationary market conditions such as an overall trend of increasing or decreasing prices, differences in availability of items or in the prices at which different items are available across time, may cause the initialization period based measure of consideration set to perform poorly. Hence, two other measures of consideration set based on more proximate purchases were defined:

i) The consideration set at each time period was defined as the set of items bought in the previous three time periods. Similar to the IT variable, IT3 was a dummy variable reflecting membership in the item based consideration set based on the previous three purchases. Also, a price based consideration set measure was defined as all items whose prices were within the range of prices paid on the three previous purchase occasions, and TR3 was defined as a dummy variable reflecting membership in this consideration set.

ii) Similar to IT3 and TR3, variables IT5 and TR5 were defined as dummy variables, reflecting membership in item-based and price-based consideration sets respectively based on the previous five purchases.[2] The five period

[2]In preliminary analysis, for dishwashing detergent and catsup, analysis was also done for another measure of consideration set membership based on the previous seven purchase occasions, using the items purchased and the prices paid, as with the three-period and five-period measures. The results were not markedly different from those for the measures based on three and five purchases, and are not presented in this dissertation.

measures would of course be expected to include more items in the consideration set than the three period measures.

Reference price measure. As identified in Chapter 3, previous research abounds in measures of reference price. The simplest and most common operationalization of reference price, as the price for the item on the previous purchase occasion, was used for the analysis of individual segments of panel members in each category, as in Gurumurthy and Little (1988), Lattin and Bucklin (1990) and Raman and Bass (1988). The "price minus reference price difference" variable used in the empirical model below will henceforth be referred to as RP.

It may be noted that the measures TR, TR3, and TR5 are all functions of prices actually paid by the consumer in the past. The reference price measure RP is a function of the prices for the items that the consumer was presumably exposed to on the previous purchase occasion. Thus, the RP measure is defined for each item in the market, while the price tier measures are defined for the consumer across the product category. This is the most important difference between the two measures. As discussed in the literature review, an anomaly in previous research in price sensitivity has been the disparity between the assumptions of the reference price models of diligent price-tracking behavior on the part of all consumers, and the findings of descriptive research that report very errorful coding of price information at the brand level. Empirical support for the TR variable that shows the variable (in any of its variants) to be more predictive of purchase behavior than RP would help resolve this apparent contradiction, as the price based consideration set membership

construct only requires consumers to code the prices actually paid for purchases in the category, not prices of all brands in the market. It may also be noted that the ranges of prices defined by the different measures of TR may vary both in width and position on the price continuum across consumers, allowing for large individual differences in price sensitivity.

Treatment of missing alternatives. A problem that is recurrent when large datasets are accumulated by combining data across consumers, stores, and markets, is that households in the panel often differ in the choice alternatives available to them at each purchase occasion. This was a serious problem in the estimation of the models for all three datasets, even though analysis was restricted to the items with the top market shares. The result of these differences in item availability across households is that price information is missing for some of the alternatives, leading to the observation being deleted from the dataset. To avoid large numbers of observations being deleted from the datasets, prices of missing alternatives were set equal to a very large number (i.e. prices were assigned to these alternatives that were so high that the alternatives would have an infinitesimal probability of purchase). All the other variables for these missing alternatives were set equal to zero. This treatment of missing alternatives led to special problems that are discussed later.

Models

The above measures of consideration set membership and reference price were incorporated into a series of nested multinomial logit models to enable

comparison against each other. For each nested sequence, item based and price based consideration set dummy variables in all the three variants--initialization period, three period and five period--were calibrated. The utility specifications were:

$$U_{ijt}=\alpha_j+\beta_1 P_{ijt}+\beta_2 PR_{ijt}+\beta_3 RP_{ijt}+\beta_4 TR_{ijt}+\beta_5 IT_{ijt}+\epsilon_{ijt} \quad 5.1$$

$$U_{ijt}=\alpha_j+\beta_1 P_{ijt}+\beta_2 PR_{ijt}+\beta_3 RP_{ijt}+\beta_4 TR3_{ijt}+\beta_5 IT3_{ijt}+\epsilon_{ijt} \quad 5.2$$

$$U_{ijt}=\alpha_j+\beta_1 P_{ijt}+\beta_2 PR_{ijt}+\beta_3 RP_{ijt}+\beta_4 TR5_{ijt}+\beta_5 IT5_{ijt}+\epsilon_{ijt} \quad 5.3$$

where u_{ijt} refers to the utility of item j for household i at purchase occasion t, α_i refers to the constant attractiveness of item j on attributes other than price and promotion, and P_{ijt} and PR_{ijt} refer to the price (measured in unit terms) and promotional status respectively, of item j for consumer i at occasion t. The error term ϵ_{ijt} is assumed to be distributed as double exponential, so that the parameters could be estimated by using a maximum likelihood procedure for a multinomial logit specification. The nested sequence of models tested for each of the segments (defined later) for the three product categories was as listed in Table 5.1. Figure 5.1 graphically depicts the various models tested.

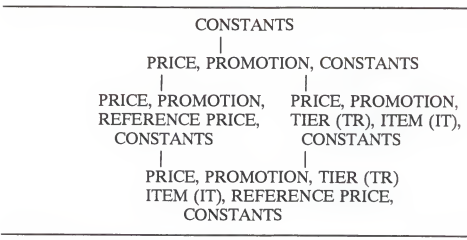
CONSTANTS
PRICE, PROMOTION, CONSTANTS
PRICE, PROMOTION, REFERENCE PRICE, CONSTANTS
PRICE, PROMOTION, TIER (TR), ITEM (IT), CONSTANTS
PRICE, PROMOTION, TIER (TR) ITEM (IT), REFERENCE PRICE, CONSTANTS

Figure 5.1. Nested sequence of models tested

The constants only model predicts probability of purchase as the respective market shares of the various items. Comparing Model 1 with this model by a likelihood ratio test will establish if there are any effects of price and promotion. Comparing models 2 and 3 against model 1 establishes whether the consideration set variables and the reference price variable (which is really the price - reference price difference) respectively add explanatory power to the model beyond the price and promotion variables. Comparing model 4 against 2 and 3 establishes whether the consideration set variables and the reference price variable add to explanatory power over each other. Similar comparisons of models 5 through 8 against model 1 and 3 and against each other would establish the usefulness of the alternate measures of the consideration set membership variable. In all these models, the coefficients of P and RP were expected to be negative, and those for all the other variables were expected to be positive.

These comparisons were done using likelihood ratio tests of the more inclusive model against the less inclusive model. The model estimates listed in the tables listed later in this chapter report a value of χ^2 for each of the models. This is the value of the test statistic for the comparison of each model against the constants only model and is calculated as

$\chi^2 = 2 \times$ ((log likelihood of the tested model) - (log likelihood of the constants only model)).

In this model, the effect of price inertia can vary considerably. The conceptual model discussed earlier specifies that items are eliminated from the consideration set based on the acceptability of the price. If this is the case, the coefficient for TR will be extremely large, as discussed in Appendix F. Moderate levels indicate that the probability of purchasing an item increases if its price is acceptable, but it is not the sole determinant of the consideration set. On several counts, this weaker model is true to the spirit of the model discussed earlier. Individual differences in price sensitivity are specified and are allowed to change over time. Consideration set membership based on both past prices and items are allowed to change over time. The measures of acceptable prices are based on prices actually paid and not just on prices observed on previous purchase occasions. Thus, the framework of the multinomial logit model is used to make comparisons between two alternate specification of the effects of lagged prices.

An empirical model "truer" to the precise mathematical formulation of the conceptual model, in terms of specifying elimination of items based on acceptable

price ranges, would not be easily amenable to the execution of such nested tests. Also, it would not permit estimation of the weaker version of the model.

Results

Results of the estimation of the nested sequence of models for each of the product categories are described next. It may be noted that for several of the datasets results for which are discussed below, the promotional effect could not be specified as some of the alternatives in the choice sets were never promoted during the period of the panel's purchases. As the promotional effect was a strong predictor of choice in the models in which it was included, the results discussed below should be interpreted very cautiously for the datasets where the effect was removed from the analysis.

Catsup. As described in the previous section, the data were divided into initialization and estimation periods, consisting of the first six purchases for each household, and the remaining purchases respectively[3]. The households were then further segmented by two different bases:

1) by the different combinations of sizes ever purchased, resulting in 19 segments that were large enough to enable estimation of multinomial logit models

[3]In order to maximize the statistical power of these analyses, no holdout sample was used. In the subsequent analyses on the combined datasets, holdout samples were used.

2) by the number of different items purchased during the initialization period, resulting in three different segments that were large enough to enable estimation of multinomial logit models.

The 22 segments obtained are described in Table 5.2. The results of the estimation for each of these segments are summarized in Tables 5.3-5.24. The tables list the estimates and z-statistics for the causal variables for each of the eight models estimated.

Purchasers of a single size. Only one of the sizes (32 ounces) had a large enough number of size-loyal households to enable estimation. Results for this segment are displayed in Table 5.3. The best fitting model for this segment was (P,PR,RP,TR,IT), which achieved a χ^2 of 198.5 (5 d.f.), though the reference price variable was not statistically significant (t=0.7) and did not increase the likelihood ratio statistic by much, with χ^2 dropping only to 197.9 (4 d.f.) for (P,PR,TR,IT). Price, promotion, and price and item based consideration set membership variables were all statistically significant predictors of item choice at the 0.05 level. The initialization measure of TR was the only measure of price based consideration set membership that was significant. The effects of price, promotion and the item-based consideration set membership variable were always significant and did not change much across the models estimated. This is the only catsup segment for which the phenomenon of size switching across time is not a concern, as the households only purchased one size throughout the period of the panel.

Purchasers of two sizes. Results for these segments are summarized in Tables 5.4-5.6. All three segments that purchased among only two sizes were "medium" size purchasers, limiting their purchases to two sizes among 28, 32, 40 and 44 ounces. For segment 2 that purchased among 28 and 32 ounce sizes, the best fitting model was (P,RP,TR5,IT5), with a χ^2 value of 926.4 (5 d.f.) though elimination of RP from this model did not significantly reduce the likelihood ratio statistic (χ^2 decreased to 925.1, with 4 d.f.). For this model, price and the item-based consideration set membership variables were significant (at the 0.05 level). Neither reference price or the price-based consideration set membership variable were significant. The effect of promotion could not be estimated for this segment, as some of the seven items that were included in the analysis were never promoted, leading to zero variance for PR for these items, and a degenerate estimate. The three-period estimate of TR performed better than TR5 for this segment, though the overall model fit for TR3 was not as good as that for TR5.

For segment 3 that purchased among 32 and 40 ounce sizes, the best fitting model was (P,PR,RP,TR,IT) which had an associated χ^2 of 60.2 (5 d.f.); elimination of RP from this model reduced the χ^2 measure to 60.2 (4 d.f.). Only price and the item-based consideration set membership variable were significant at the 0.05 level. Only four items were included in this analysis, and the model was estimated on just 35 observations.

For segment 4 that purchased among 32 and 44 ounce sizes, the best fitting model was (P,PR,RP,TR3,IT3) with an overall χ^2 of 91.4 (5 d.f.); without RP, the

measure decreased imperceptibly. Surprisingly, the price tier measure TR3 was significantly negative (at the 0.05 level), perhaps suggesting that members of this segment were size switchers, as the prices they paid exhibited great variance. Not surprisingly, the price coefficient for this model was not significant. Promotion and IT3, the three-period item based consideration set membership variable were also significant.

Purchasers of three sizes. Tables 5.7 to 5.11 present results for five segments for panel members who purchased among three different sizes. These segments accounted for almost half the total number of observations from the 19 "size" segments.

For segment 5, members of which purchased among 14, 28 and 32 ounce sizes, the best fitting model was (P,PR,RP,TR5,IT5), which achieved a χ^2 of 1243.1 (5 d.f.). Promotion, reference price, and price and item based measures of consideration set membership were all significant at the 0.05 level, but price was not. This was one of the few segments for which the magnitude of the z-statistic for the price-based consideration set membership variable was comparable to that for the item-based measure. For the model (P,PR,TR5,IT5), the z-statistic for TR5 (9.1) was higher than that for IT5 (7.1). Across the six runs in which the consideration set membership variables were included, price was an insignificant predictor. It is interesting to note that price was a significant predictor when the only other variables were promotion and reference price.

For segment 6 (the second ranking segment in size among the 19 segments), members of which purchased among 28, 32 and 40 ounces, the best fitting model was (P,RP,TR3,IT3); χ^2 for this model was 1834.4 (4 d.f.). Promotion could not be included in this model as some of the items were never promoted during the estimation period. All four variables were significant at the 0.05 level.

For segment 7, members of which chose from among 28, 32 and 44 ounce sizes, the best fitting model was (P,PR,RP,TR3,IT3), the overall χ^2 for which was 579.2 (5 d.f.). Reference price and the item-based consideration set variables were significant at the 0.05 level. The price based consideration set membership variables were significant for the two other measures based on the initialization period and on the previous five periods.

For segment 8, members of which purchased among sizes 28, 32 and 64 ounces, the best fitting model was (P,PR,RP,TR5,IT5), the χ^2 for which was 3077.6 (5 d.f.). All five variables were significant predictors, with promotion having the largest effect among the three dummy variables, PR,TR5 and IT5. This was the largest of the 19 catsup "size" segments for which the nested sequence of models was estimated. The overall likelihood ratio statistic was not much worse for the three-period measures. The χ^2 measure for the model (P,PR,RP,TR3,IT3) was 3076.2 (5 d.f.).

For segment 9, members of which restricted purchases to sizes 32, 40 and 44 ounces, the best fitting model was (P,PR,RP,TR3,IT3). The likelihood ratio statistic of χ^2 for this model was 154 (5 d.f.). For this model, price, promotion, and item-

based consideration set membership variables were significant. All three measures of price-based consideration set membership performed poorly.

Purchasers of four sizes. Estimates for segments that purchased among four sizes are presented in Tables 5.12 to 5.17. Observations for these segments accounted for 30% of all observations.

For segment 10, members of which restricted purchases to 14, 28, 32 and 40 ounces sizes, the best fitting model was (P,PR,RP,TR3,IT3); χ^2 for this model was 544.8 (5 d.f.). All variables except price were significant at the 0.05 level. The measure of price-based consideration set membership was significant across the three definitions for this segment.

Members of segment 11 made purchases among sizes 14, 28, 32 and 44 ounces. The best fitting model for this segment was (P,PR,RP,TR3,IT3), for which the χ^2 likelihood ratio statistic was 291.9 (5 d.f.). Promotion, reference price and the item-based consideration set membership variable were significant at the 0.05 level. The price based measure of consideration set membership was not a significant predictor for any of the three definitions.

Segment 12 was composed of panel members who purchased from the medium sizes only (28,32,40 and 44 ounces) and was the largest of the segments that made purchases among four sizes. The best fitting model for these consumers was (P,RP,TR3,IT3); the likelihood ratio statistic for this model was a χ^2 value of 1699.7 (4 d.f.). The estimate for promotion could not be estimated as some of the items were never promoted during the estimation period. The four variables included were

all significant at the 0.05 level. The fit of the model with the five period measures was very similar.

Segment 13 members made purchases from sizes 28,32,40 and 64 ounces. The best fitting model for these consumers was (P,PR,RP,TR3,IT3), the χ^2 value for which was 1065.0 (5 d.f.). The variables other than TR3 were all significant at the 0.05 level. The five period measure of TR was significant, though the general likelihood ratio statistic of the five period model was not as high with a χ^2 value of 1048.8 (5 d.f.).

The best fitting model for segment 14 whose members purchased among sizes 28,32,44 and 64, was (P,PR,RP,TR3,IT3); the χ^2 measure for this model was 546.2 (5 d.f.). Again, other than TR3, the variables in the model were all significant predictors of item choice. The TR variable was not a significant predictor in any of its measured forms.

Segment 15 was composed of panel members who purchased among the larger sizes, 32, 40, 44 and 64 ounces. The best fitting model for this segment was (P,PR,RP,TR5,IT5); the likelihood ratio statistic for this model was a χ^2 value of 132.5 (5 d.f.). Promotion, and the two consideration set membership variables based on price and item were significant at the 0.05 level. This was one of the few segments for which the price-based version was "stronger" (as reflected in a larger z-statistic for the estimated coefficient) than the item based measure - the z-statistics for the two measures were 3.1 and 2.5 respectively.

Purchasers of five sizes. Results of estimating the nested sequence of models for the three segments that purchased among five sizes are presented in Tables 5.18 to 5.20.

Segment 16 members purchased from sizes 14,28,32,40 and 44 ounces. The best fitting model for these consumers was (P,RP,TR3,IT3)--the χ^2 value for likelihood ratio statistic was 402.7 (4 d.f.) for this model. All four included variables were significant predictors at the 0.05 level. The z-statistic for the price-based measure of consideration set membership was higher (at 3.2) than that for the item based measure (for which the z-statistic was 2.9).

Segment 17 was composed of members who purchased from sizes 14, 28, 32, 40 and 64 ounces. The best fitting model for this segment was (P,PR,RP,TR5,IT5) and had a χ^2 value of 302.8 (5 d.f.). All five included variables were significant at the 0.05 level. Between the initialization period measures, TR performed much better than IT, indicating that for this segment, prices paid in the initialization period were better predicted future purchases than the items purchased in the initialization period.

Segment 18 had panel members who purchased among 28,32,40,44 and 64 ounces. The best fitting model for this segment, largest of the five-size purchasing segments, was (P,RP,TR3,IT3); the likelihood ratio statistic for this model was 1792.6 (4 d.f.). The coefficient of promotion could not be estimated for this segment as some of the items were never promoted, causing the promotion coefficient to degenerate. The four coefficients of the "causal" variables were all significant at the

0.05 level. The fit was not much worse for the next best fitting model (P,RP,TR5,IT5), for which the χ^2 value was 1788.4 (4 d.f.).

Purchasers of six sizes. Table 5.21 summarizes the results of estimating the nested set of models for the segment that purchased at least one of all six sizes 14, 28, 32, 40, 44 and 64 ounces. The best fitting model for this segment was (P,PR,RP,TR3,IT3), the likelihood ratio statistic for which was 550.1 (5 d.f.). All five included "causal" variables were significant at the 0.05 level. The pattern of coefficients and the χ^2 value, 548.2 (5 d.f.) were very similar for the model (P,PR,RP,TR5,TR5). As for segment 17, between the initialization period measures, TR was a better predictor than IT, indicating that for this segment too, prices paid in the initialization period were a better predictor of items chosen in the estimation period than were items purchased in the initialization period.

The other basis of segmentation, the number of items purchased in the initialization period (of the first six purchases), resulted in three segments that had a sufficient number of observations to estimate parameters. Segment 20 purchased one or two different items in the initialization period, and may hence be interpreted as an item-loyal segment. Segments 21 and 22 purchased 3 and 4 items respectively in the initialization period. As some of the items were never promoted during the estimation period, the promotion coefficient tended to degenerate, and hence was not estimated for any of these segments. Tables 5.22 to 5.24 summarize the results for these segments.

Purchasers of one or two items. The best fitting model for segment 20, members of which purchased one or two items in the initialization period, was (P,RP,TR5,IT5). The χ^2 value for likelihood ratio statistic was 1237.9 (4 d.f.). All the included variables were significant at the 0.05 level. The models with the other measures of TR and IT resulted in a similar pattern of coefficients.

Purchasers of three items. The best fitting model for segment 21, (largest of these three "number-of-items" segments), members of which purchased three items in the initalization period, was (P,RP,TR5,IT5); the likelihood ratio statistic for this model was a χ^2 value of 8595.5 (4 d.f.). Again, the included variables were all statistically significant at the 0.05 level. The z-statistic for price decreased greatly in magnitude upon inclusion of the TR and IT variables, in all their three measures.

Purchasers of four items. The best fitting model for segment 22, members of which purchased four items in the initialization period was (P,RP,TR3,IT3). The likelihood ratio statistic for this model was a χ^2 value of 3456.4, and again, all four included variables were significant predictors. As for the previous segment, the pattern of coefficients was similar across the three measures of TR and IT, and the z-statistic for the price variable decreased in magnitude upon inclusion of the consideration set membership variables.

The best fitting models for each of the 22 segments discussed are summarized in Table 5.43.

Yogurt. The division of the data for yogurt into subgroups resulted in 7 datasets. Results for these datasets are summarized in Tables 5.26-5.32.

Purchasers of 6 ounce containers. Across the two markets, for segment 1, consisting of purchasers loyal to six ounce containers, the best fitting model was (P,PR,RP,TR3,IT3). The likelihood ratio statistic for this model was a χ^2 value of 574.9 (5 d.f.). Eliminating RP from this model did not reduce the χ^2 measure significantly (the measure decreased to 573.6 with 4 d.f.), and correspondingly, the reference price measure was not significant in the best fitting model. Price, promotion, and both price and item based measures of consideration set membership were significant. The magnitudes of the z-statistics were very similar for the corresponding models with the three-period measures, although the χ^2 value was lower, at 559.2 (5 d.f.).

Purchasers of 8 ounce containers - market 1. Market 1 consisted of panel members who confined their shopping for yogurt to a particular chain. For segment 2, that consisted of consumers in this market who were "loyal" to eight-ounce containers of yogurt, the best fitting model was (P,PR,RP,TR5,IT5), which had a likelihood ratio statistic of a χ^2 value of 376.4 (5 d.f.). As for segment 1, the reference price did not contribute significantly to the likelihood ratio statistic. The other variables P, PR and the price and item-based consideration set membership variables were all significant at the 0.05 level. The pattern of results was very similar for the three-period measures, with the χ^2 value not much less at 373.6 (5 d.f.).

Purchasers of 8-ounce containers - market 2. For segment 3 which consisted of consumers in Market 2 who confined their purchases to 8 ounce containers, the best fitting model was (P,PR,RP,TR3,IT3), which had a χ^2 value of 495.4 (5 d.f.).

Eliminating RP from this model did not significantly reduce the fit of the model. Price and item based consideration set membership variables were significant as were price and promotion. As for the earlier segments, a similar pattern of results were obtained for the five-period measures

The other four segments were defined with the number of items purchased in the initialization period as the basis of segmentation. Results for these segments are presented in Tables 5.29 to 5.32. As with the catsup segments, estimation of the coefficient of promotion was impossible as some of the items were never promoted.

Purchasers of one or two items - market 1. For segment 4, the best fitting model was (P,RP,TR,IT), which had a χ^2 value of 224.1 (4 d.f.). This was the only segment of yogurt purchasers for which the initialization period measures fitted best. Only price and item-based consideration set membership variables were significant. The price based measure was significant for the five-period version, but the overall fit of that model was lower at 209.6 (4 d.f.).

Purchasers of one or two items - market 2. For segment 5 that consisted of panel members in market 2 that purchased one or two items in the initialization period, the best fitting model was (P,RP,TR3,IT3); the χ^2 likelihood ratio statistic for this model was 484.3 (4 d.f.). As for the other market, only price and the item-based consideration set variables were significant predictors of item choice. The other variants of the item based measure also had coefficients of similar magnitude, but none of the three versions of the price based measure were significant.

Purchasers of three or more items - market 1. The best fitting model for segment 6 was (P,RP,TR3,IT3) which had a χ^2 value of 75.3 (4 d.f.), though the fit decreased only imperceptibly when RP was dropped from the model. The only variable that was statistically significant at the 0.05 level was the item based measure of consideration set membership. The initialization period measure and the five period measure of price based membership were significant predictors when compared against the corresponding versions of the item based measures.

Purchasers of three or more items - market 2. The two models with the initialization period measures of the consideration set membership variables did not converge within forty iterations. This degeneracy was possibly because of the extremely small sample size of 35 observations. Of the remaining models, the best fitting was (P,RP,TR3,IT3) which had a χ^2 value for likelihood ratio statistic of 33.4 (4 d.f.). Only the two consideration set membership variables were significant for this model.

The best fitting models for yogurt are summarized in Table 5.44. It may be noted that in the best fitting models for the "size" segments 1, 2 and 3, TR has the highest z-statistic of the three price-related variables.

Dishwashing detergent. Subdivision of data for dishwashing detergent resulted in nine segments. The estimates for the nested sequence of models for each segment are summarized in Tables 5.34-5.42.

Purchasers of single sizes. Segment 1 was the only segment of a reasonable size that restricted purchases to a single size, 12 ounces. The best fitting model for

this segment was (P,RP,TR5,IT5), the χ^2 value for which was 176.0 (4 d.f.). The coefficient for promotion could not be estimated for this segment, as some of the 12 ounce items were never promoted during the estimation period. The item based consideration set membership variable was the only significant predictor for this segment.

Purchasers of two sizes. Tables 5.35 and 5.36 present the estimates for segments that purchased two sizes.

Segment 2 consisted of panel members who purchased 12 and 22 ounce size items. The best fitting model for this segment was (P,PR,RP,TR5,IT5), the likelihood ratio statistic for which was 948.2 (5 d.f.). Eliminating RP from this model did reduce the χ^2 value by much. The other included variables, price, promotion, and price and item based consideration set membership variables were all significant. The three-period measure of price-based consideration set membership was also significant, but the three period model achieved a much lower χ^2 value.

The best fitting model for segment 3 which was composed of panel members who purchased 22 and 32 ounces was (P,RP,TR,IT), the model that used the initialization period measures of item and price based consideration sets. The χ^2 value for this model was 163.1 (4 d.f.). Promotion effects could not be estimated as some of the brand sizes were never promoted. Price and item-based consideration set membership variables were the only significant predictors of item choice.

Purchasers of three sizes. Tables 5.37 and 5.38 present results of estimating the models for segments of consumers who purchased three sizes.

For segment 4, members of which purchased the smaller three sizes, 12, 22 and 32 ounces, the best fitting model was (P,PR,RP,TR5,IT5). The χ^2 likelihood ratio statistic for this model was 932.2 (5 d.f.). Price, promotion, reference price and the item based measure of consideration set membership were significant at the 0.05 level. For the initialization period measure of price-based consideration set membership, the coefficient was significantly negative, suggesting that prices may have increased or decreased across the items purchased by this segment over the period of the sample.

The best fitting model for segment 5 members of which purchased among the medium sizes, 22,32 and 48 ounces, was (P,RP,TR5,IT5). The likelihood ratio statistic for this model was a χ^2 value of 727.8 (4 d.f.). The promotion effect could not be estimated for this segment too. The other variables included in the model were all significant at the 0.05 level.

Purchasers of four sizes. Segment 6 consisted of panel members who purchased among sizes 12,22,32 and 48 ounces. The best fitting model for this segment, which had only 41 variables available for estimation was (P,RP,TR5,IT5), with a χ^2 value of 43.3 (4 d.f.). The item based measure of consideration set membership was the only variable whose coefficient was significant at the 0.05 level. Promotion effects could not be estimated for this model, as some items were never promoted during the estimation period.

For the other basis of segmentation--the number of items purchased in the initialization period--the measure of item based consideration set membership tended

to cause the model to degenerate for all three measures for the segments that purchased one or two items, and three items. Consequently, for these segments 7 and 8, only the reference price versus price tier comparison was of interest. All three variables could be compared for segment 9 composed of panel members who purchased as many as four or five items in the initialization period.

For members of segment 7 who purchased only one or two different item sizes in the initialization period, the best fitting model among those that did not include the measure of item based consideration set membership was (P,RP,TR5), the χ^2 value of likelihood ratio statistic for which was 1553.0 (3 d.f.). All three variables included were significant at the 0.05 level. The z-statistic for the price variable dropped appreciably when the price based consideration set membership variable was added to the specification (from -5.4 to -3.4). The decrease in the coefficient was less for the addition of the reference price measure was not as great (from -5.4 to -5.3). The price based measure of consideration set membership was significant for all three variants.

For members of segment 8 who purchased three items in the initialization period, the best fitting model among those that did not include the item based consideration set measure was (P,RP,TR5). The χ^2 measure for goodness of fit was 1036.4. All three included variables were significant. The TR variable was a significant predictor for all three variants of the measure.

The best fitting model among consumers who purchased four or five items in the initialization period (who constituted segment 9) was (P,RP,TR5,IT5). The

likelihood ratio statistic for this model was 978.5 (4 d.f.). All four included variables were significant at the 0.05 level. The magnitudes of the estimated z-statistics were similar for the three-period measures, but the overall level of fit was lower, with a χ^2 value of 908.5.

Discussion. There were certain consistent results across all the segments for all three categories. The most consistent predictor of item choice across all the analyses was the item-based consideration set membership variable. For every segment, the best fitting model included some variant (the initialization period measure IT or the three-period or five-period measures IT3 and IT5) of the measure of this variable that was a significant predictor. The implications of this result for modelling choice data, and the process by which this variable affects choice model predictions are discussed in the final chapter. Promotional status was another variable that was always statistically significant when it was included in a specification. However, the variable was dropped from the analyses for several of the segments for reasons discussed earlier. In the models in which promotion was included as a causal variable, the z-statistics for it and for the item based consideration set membership variable were usually the largest, indicating that these were the most stable predictors.

The price variable was significant for three-fourths of the segments for each of the three categories. However, the estimate was biased downward for several segments, because of the treatment of the prices of missing alternatives, as discussed in the "Problems" section below. An interesting effect that was found across the segments was that the inclusion of the dummy variables for consideration set

membership reduced the magnitude of the z-statistic for the price variable. This effect did not occur when only reference price was added to the model, even when the reference price variable added significantly to the likelihood ratio statistic. A reason for this phenomenon may be that the presence of the dummy variables for consideration set membership controls for the bias in price estimates when the consideration set is misspecified.

The segmentation of the populations of heavy users of the three categories by the sizes that the members purchased was done to isolate the price tier effects from size switching effects. However, this procedure resulted in only one segment of catsup purchasers, two segments of yogurt purchasers and one segment of dishwashing detergent purchasers who confined their purchases to just one size. For catsup, for the segment that purchased only the 32 ounce container, the price-based consideration set membership variable was significant in the best fitting model, while the reference price specification was not. The result was repeated for the 6 ounce segment of yogurt purchasers and for the eight ounce purchasers in both markets. For dishwashing detergent, neither reference price nor price-based consideration set membership were significant predictors in the "best" specification for the 12 ounce loyal segment.

Across the other size-defined segments, there was no consistent pattern of superiority of the two alternate specifications of adaptation effects. The price based consideration set membership variable performed best for yogurt, where it was a significant predictor, and reference price was not significant for all three size

segments. The initial period measure of the acceptable price range was not as good a predictor of the acceptable price range in the estimation period, as the more purchase-proximate three period and five period measures.

In general, for catsup, the two different period measures of item-based and price-based consideration set membership variables did equally well in predicting choice. For all the segments the five period measure did well, the three period measure did not result in a much lower level of likelihood ratio statistic. The three period measures performed better for yogurt, and the five period measures for dishwashing detergent.

The purpose of the other base of segmentation was to determine if the phenomenon of acceptable price ranges was more valid for brand switchers as compared to "brand loyals". A problem with interpreting the results for these datasets is that promotional effects were often not estimable. There was no support for this hypothesis for the catsup segments. The relative sizes of the item-based consideration set membership variable effects and the price based variant were approximately the same for both the segment that purchased 1 or 2 items in the first six purchases, as for those that purchased four different items in the initial period. For yogurt, though, the hypothesis did seem to hold, especially for market 2, for which the item based consideration set membership variable was not significant for the segment that purchased more than two different items in the initialization period, while the corresponding price based variable was. For the segment that purchased only one or two items in the initialization period, both variables were significant and

of comparable magnitudes. The coefficient of the item based consideration set variable degenerated for the item loyals (those that purchased one or two items) for detergent, and this comparison could not be made.

Problems caused by missing or zero observations. There were two recurrent problems that occurred for the segment-wise analysis for all three product categories. The promotional status variable PR proved to be a significant predictor of item choice whenever it was included in the specification. It was the variable with the largest estimated z-statistic. In several of the segments though, some of the items purchased were never promoted, leading to zero variance for the promotional status variable, and hence perfect collinearity with the item constant. In such cases, the algorithm used (PROC MLOGIT, written by Salford Systems, for the Statistical Analysis Software program) dropped the variable from the analysis, and estimated the model with the remaining variables, as the Hessian of the log likelihood function tended toward singularity. The standard error for the PR coefficient was assigned value zero and the z-statistic degenerated. For all these segments, thus, the models were estimated without an important "known" significant predictor. This happened for six of the nineteen "size" segments for catsup, and for four of the six "size" segments for dishwashing detergent. It also happened for all the segments defined on the other basis of segmentation (number of items in the initialization period) for both catsup and dishwashing detergent, and for all but one of the four yogurt segments.

The other recurrent problem was that the stores in the datasets often differed widely in the items that were available. Thus for any segment that had members that purchased from different stores (or even different cities), some of the items were unavailable throughout the period of the sample, and some other items varied in their availability through the period of the sample. This led to several missing prices in the dataset. Estimating the models with these missing prices would result in eliminating choices, for which any of the prices were missing, and a much reduced dataset. Since the analysis was confined to the major share items, it was expected that the availability of items would not be a serious issue for the majority of the observations. The unavailability was sought to be represented in the data by setting the price of the missing items at an extremely large value, and all other values to zero. It was hoped that the structure of the multinomial logit specification would enable this modification to correctly eliminate the offensive items from the estimation for the appropriate choices, and would not bias the estimates of the price parameter. It may be noted that the consideration set membership variables are not prey to this problem. Non-availability of an item is easily captured by the setting of the consideration set membership dummy variables equal to zero. The estimates revealed that the modification of the prices of the unavailable items did bias the price estimates downward. When prices were set extremely high, the coefficient of price estimated was extremely low. For segments for which the price coefficient was estimated as positive, the models were re-estimated without observations for which any of the prices were missing. Seventeen of the twenty-two catsup segments, and six of the

nine dishwashing detergent segments were subject to this problem of biased price estimates. For yogurt, the difference in availability of items varied so much across the two markets for the eight-ounce containers that analysis was separately done for the two markets for the eight-ounce loyal consumers. Consequently, biased price coefficients were not a problem for the yogurt segments.

These recurrent problems were sought to be resolved by aggregating the observations across the segments, and re-estimating the models for all three categories. The increased sample size enabled the retention of observations for which all prices were available to still leave a reasonable sample of observations to estimate the models. Also, households who purchased items that were never promoted were eliminated from the sample to resolve the problem of zero variance for the promotional dummy variable for any of the items in the analysis. The results of the estimation of the models for these larger samples are presented in Tables 5.46 to 5.53.

Analyses for Aggregated Datasets

The set of measures tested in the exploratory stage were augmented by refined measures of item-based consideration set membership, and reference price.

Alternate Measures

The measure of item-based consideration set membership was refined by separating the effects of brand-inertia and size-inertia. Two new dummy variables

BD, and SZ were defined to represent membership in consideration sets predicted by the brands and sizes purchased respectively in the initialization period. Variables BD3, SZ3, BD5 and SZ5 were defined similar to the three-period and five-period measures of TR and IT. An alternate measure of reference price was also tested. Reference price was measured as a weighted log mean of the previous three period's prices, following Kalwani et al (1991), and Helson(1964). The measure was specified thus:

$$EXP\sum_{m=1}^{3} \frac{\rho^{m-1} \ln(P_{ijt-m})}{\sum_{m=1}^{3} \rho^{m-1}}$$

The parameter ρ was set at 0.25, as in Kalwani et al (1991). It may be noted that RP is a special case of RP3, with ρ set equal to zero. The "reference price minus price" difference for this threee-period measure will be referred to as RP3 henceforth. This difference was tested against the corresponding three period measures of item-based and price-based consideration set membership variables.

Models

The sequence of nested models estimated in the exploratory stage was also augmented to include models which estimated the effects of the price-based consideration set membership and the item-based consideration set membership variables separately from each other. The new measures of brand-based and size-

based consideration set membership variables were also included in a set of nested models that tested the effects of these variables and the price-based measure, against the reference price specification, for each of the alternate definitions of these new measures. The three-period measure of reference price was tested against the three-period measure of price-based consideration set membership. Finally, the datasets were split into estimation and holdout samples, and tests of predictive validation were carried out for these alternate three-period measures, RP3 and TR3.

Results

The results of the estimation of the new nested sequence of models and the predictive validation tests are discussed in this section.

The store items and one other item that was never promoted were dropped from the analysis and the data aggregated across all catsup segments for all observations for which price information was not missing for any of the items. The results of the analysis are summarized in Table 5.46. The best fitting model was (P,PR,RP,TR5,IT5), for which the likelihood ratio statistic of χ^2 was 1291.0 (5 d.f.). The likelihood ratio statistic dropped only to 1290.8 (4 d.f.) when RP was eliminated from this model. Both price and item based consideration set membership variables were significant predictors, as were price and promotion. The three period measure of acceptable price range was also a significant predictor. Reference price was a significant predictor in the models (P,PR,RP) and (P,PR,RP,TR,IT), but not when included with the three period measures of the consideration set variables.

For yogurt, for market 1, the best fitting model was (P,PR,RP,TR3,IT3), for which the χ^2 value was 440.2 (5. d.f.), and which did not decrease significantly when reference price was dropped from the analysis. The other four variables were all significant predictors. The same results were true for market 2.

For dishwashing detergent, the best fitting model was the one with the five-period measures, the χ^2 value for which was 1544.2 (5 d.f.). Reference price was significant for this model (P,PR,RP,TR5,IT5), as were promotion and the consideration set variables. Interestingly, for the detergent dataset, the alpha level of significance of the price coefficient dropped to below 0.05 when promotion, reference price and the consideration set variables were added to the specification.

Separating size inertia from brand inertia. The choice alternatives in all the models discussed thus far were specified in terms of brand-size combinations. The variables IT,IT3 and IT5 thus have tracked the effects of brand-size inertia, not just the tendency to purchase the same brand over time. For the aggregated dataset, since all the size groups were combined, and five or more sizes were included in the analysis, variables BD and SZ, were specified (corresponding to IT) to define consideration sets based separately on the brands and sizes purchased in the initialization period. The variable BD thus measured the tendency to purchase the same brand over time, while SZ measured the tendency to purchase the same size over time. Variables BD3, SZ3 and BD5, SZ5 were defined as similar analogs of the three period and five period measures of item and price based consideration set measures. These variables were included in the utility specifications with price,

promotion and the corresponding price-based consideration set measure, and then with the addition of reference price, and the models were re-estimated for all the three categories. The results are summarized in Tables 5.47, 5.49, 5.51 and 5.53.

The best fitting model for catsup for the previous measures of item-based consideration set was (P,PR,RP,TR5,IT5). Separating brand inertia from size inertia in the model (P,PR,RP,TR5,BD5,SZ5) reduced the level of fit from a χ^2 value of 1291.0 (5 d.f.) to 1252.1 (6 d.f.). Brand and size inertia were both significant predictors in the new model, and reference price again did not add significantly to the fit. The price based measure of consideration set membership remained a significant predictor of item choice, though with a smaller coefficient, as did the item-based consideration set membership measure.

The best fitting model for both markets of yogurt consumers for the previous measures was the one with the three-period definitions of price and item based consideration sets. For both these markets, the three period measures of brand and size inertia measured separately were again the best fitting among the three variants tested. As for catsup, the split did not add to the overall likelihood ratio statistic. Similarly, reference price was not a significant predictor, and the price based consideration set measure remained a significant predictor, though with a slightly reduced coefficient. The z-statistics for the size inertia measures for yogurt were not as large as those for catsup, perhaps because there were only two different sizes in the yogurt analysis, while there were six different sizes for catsup. The coefficient of

the item based consideration set measure also decreased slightly, but remained a strong predictor of item choice.

The best fitting model for dishwashing detergent with the previous measures was (P,PR,RP,TR5,IT5). For the new measures separating brand from size inertia, the three period measures had the better fit, and even improved upon the previous measures, with a χ^2 value of 1653.6 (6 d.f.) compared to 1544.2 (5 d.f.). Size inertia contributed significantly to the likelihood ratio statistic (there were five different sizes among the choice alternatives) as did price and brand inertia. Unlike catsup and yogurt, for dishwashing detergent, the reference price specification was a significant predictor in the best fitting model. Interestingly, for the best fitting model with the three-period measures of the three inertia constructs, the coefficient of price was not significant.

Alternate measure of reference price. The models discussed thus far have included different measures of price based consideration set membership. Since reference price was always measured as a one-period lag of observed price, and the price based consideration set measures spanned more periods, a fairer comparison between the two alternate measures of lagged effects (RP measured at the item level, and TR measured at the product category level) might include more periods of lags for the reference price specification[4]. Accordingly, the three-period measure of

[4]It must be noted though that even the single period lagged reference price definition is defined at the brand level, and hence for a model with n brand choices, n pieces of lagged information are incorporated into the reference price coefficient. For the three period definition of price based consideration set membership, only three pieces of information are used.

acceptable prices for the category was contrasted with a three period lagged specification of reference price (where the reference price measure was a weighted log mean of the previous three prices, as defined earlier in this section). The results are presented in Tables 5.47, 5.49, 5.51 and 5.53.

The three-period definition of reference price was statistically significant (at the 0.05 level) for catsup, improving upon the performance for the single period lag. The overall level of likelihood ratio statistic, a χ^2 value of 1272.3 (5 d.f.) was also slightly better than that for the single period definition, of 1268.2 (5 d.f.). The price-based consideration set membership definition was also significant for this model. The new measure of reference price was not significant in the presence of the item and size based consideration set membership variables in the model (P,PR,RP3,TR3,BD3,SZ3).

The new definition of reference price was not a significant predictor of item choice for the two yogurt markets, and did not affect the parameters of any of the other variables. The χ^2 values of likelihood ratio statistic were very similar for both measures of reference price, for each of the markets.

The addition of two periods of lags to the reference price definition did not add much in terms of likelihood ratio statistic to the best fitting detergents model. Reference price remained a significant predictor, with a small enhancement in sizes of both the coefficient and the z-statistic. The best fitting model was (P,PR,RP3,TR3,BD3,SZ3) with an overall χ^2 value of 1655.5 (6 d.f.). Except for

price, all independent variables in this model were statistically significant at the 0.05 level.

Predictive tests. Finally, the alternate three period measures were also tested for predictive power. Each of the four combined sets of observations (for catsup, for the two yogurt markets, and for dishwashing detergent) were split into estimation and holdout samples, and the estimates obtained in the first period were used to predict the choices in the second period. Predicted log likelihoods and the success rates for item choice predictions based on the "first choice" criterion (the predicted choice was the item with the greatest utility) for the two alternate models are presented in Table 5.54. The predictive abilities of the two measures (RP3 and TR3) were not very different, though the TR3 measure performed slightly better than the RP3 measure, for catsup and the two yogurt datasets on the log likelihood criterion.

The model (P,PR,TR3,IT3) achieved a predicted log likelihood of -205.1 and a prediction success rate of 59% for the holdout sample, for catsup, both slightly higher than for the model (P,PR,RP3,IT3), which had a predicted log likelihood of -210.7, and a prediction success rate of 57%.

The predictive validation tests did not reveal large differences in log likelihoods, or in prediction success rates for each of the yogurt markets (which were fairly high, at around 71% for the first market, and 89% for the second market).

The log likelihoods for the predicted choices for the holdout sample for dishwashing detergent were -569.8 for the model (P,PR,RP3,IT3) and -570.8 for (P,PR,TR3,IT3). The prediction success rate was 46% for both models.

For all three categories, the two alternate measures of reference price and price based consideration set membership added nothing in terms of the success rate of the first choice criterion, over that contributed by price, promotion and the item-based consideration set membership variable.

Table 5.1 Nested sequence of models tested

Model	P	PR	RP	TR	IT	TR3	IT3	TR5	IT5
1	x	x							
2	x	x	x						
3	x	x		x	x				
4	x	x	x	x	x				
5	x	x				x	x		
6	x	x	x			x	x		
7	x	x						x	x
8	x	x	x					x	x

Table 5.2 Catsup segments

Segment	Description	Number of Observations	Number of Brands
	Sizes Purchased		
1	32 oz	144	4
2	28,32 oz	715	7
3	32,40 oz	35	4
4	32,44 oz	57	6
5	14,28,32 oz	777	8
6	28,32,40 oz	1620	8
7	28,32,64 oz	496	8
8	28,32,44 oz	1740	9
9	32,40,44 oz	107	7
10	14,28,32,40 oz	318	9
11	14,28,32,44 oz	173	8
12	28,32,40,44 oz	1451	10
13	28,32,40,64 oz	610	9
14	28,32,44,64 oz	343	10
15	32,40,44,64 oz	98	7
16	14,28,32,40,44 oz	238	10
17	14,28,32,40,64 oz	192	8
18	28,32,40,44,64 oz	1303	11
19	14,28,32,40,44,64 oz	318	11
	Number of Brands in Initial Period		
20	1 or 2 brands	709	9
21	3 brands	5755	12
22	4 brands	2531	12

Table 5.3 Estimates for catsup segment 1 (32 oz)
(n=144, nob=4, null log likelihood=-199.6)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-161.8 (-2.3)	3.1 (5.9)				137.3
P,PR,RP	-192.5 (-2.4)	3.1 (6.0)	44.7 (1.0)			138.2
P,PR,TR,IT	-285.1 (-3.4)	3.1 (5.5)		1.0 (2.8)	1.8 (5.3)	197.9
P,PR,TR,IT,RP	-305.4 (-3.4)	3.2 (5.4)	36.1 (0.7)	0.9 (2.8)	1.8 (5.3)	198.5
P,PR,TR3,IT3	-230.9 (-2.8)	3.1 (5.5)		0.3 (0.9)	1.5 (5.3)	180.7
P,PR,TR3,IT3,RP	-245.1 (-2.7)	3.2 (5.5)	21.3 (0.4)	0.3 (0.9)	1.4 (5.2)	180.9
P,PR,TR5,IT5	-197.5 (-2.4)	3.4 (5.7)		0.4 (1.1)	1.7 (5.4)	184.1
P,PR,TR5,IT5,RP	-225.2 (-2.5)	3.4 (5.7)	41.5 (0.9)	0.4 (1.1)	1.7 (5.3)	184.9

Note. In this and all the succeeding tables, n refers to the number of observations, nob to the number of brand-sizes, and the null log likelihood to the log likelihood for the constants only model. The figures in parentheses are z-statistics.

Table 5.4 Estimates for catsup segment 2 (28,32 oz)
(n=715, nob=7, null log likelihood=-1391.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-203.3 (-11.0)					750.4
P,PR,RP	-208.9 (-10.1)		7.9 (0.6)			750.8
P,PR,TR,IT	-218.1 (-11.3)			-0.1 (-1.0)	1.3 (11.7)	907.9
P,PR,TR,IT,RP	-219.0 (-10.2)		1.3 (0.1)	-0.1 (-1.0)	1.3 (11.7)	908.0
P,PR,TR3,IT3	-199.4 (-10.3)			0.3 (2.3)	1.1 (11.6)	922.6
P,PR,TR3,IT3,RP	-186.3 (-8.7)		-18.2 (-1.4)	0.2 (2.1)	1.2 (11.6)	924.6
P,PR,TR5,IT5	-196.8 (-10.2)			0.0 (0.3)	1.4 (12.3)	925.1
P,PR,TR5,IT5,RP	-186.3 (-8.7)		-14.7 (-1.1)	0.0 (0.2)	1.4 (12.3)	926.4

Table 5.5 Estimates for catsup segment 3 (32,40 oz)
(n=35, nob=4, null log likelihood=-48.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-297.3 (-2.9)	1.4 (1.7)				43.2
P,PR,RP	-327.6 (-2.7)	1.4 (1.8)	46.9 (0.6)			43.5
P,PR,TR,IT	-400.4 (-2.9)	1.3 (1.2)		-1.1 (-1.0)	5.1 (3.1)	60.2
P,PR,TR,IT,RP	-469.8 (-2.7)	1.3 (1.2)	78.6 (0.8)	-0.9 (-0.8)	5.1 (3.1)	60.8
P,PR,TR3,IT3	-350.2 (-2.8)	0.9 (0.9)		-0.3 (-0.4)	2.1 (2.9)	55.6
P,PR,TR3,IT3,RP	-371.1 (-2.6)	0.9 (1.0)	28.6 (0.3)	-0.2 (-0.3)	2.0 (2.8)	55.7
P,PR,TR5,IT5	-327.0 (-2.7)	1.2 (1.4)		0.6 (0.8)	1.5 (2.0)	53.2
P,PR,TR5,IT5,RP	-372.3 (-2.6)	1.3 (1.4)	52.9 (0.6)	0.6 (0.9)	1.5 (2.0)	53.6

Table 5.6 Estimates for catsup segment 4 (32,44 oz)
(n=57,nob=6,null log likelihood=-102.1)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-178.2 (-1.4)	3.6 (2.9)				65.4
P,PR,RP	-169.4 (-1.3)	3.6 (2.9)	-15.4 (-0.3)			65.4
P,PR,TR,IT	-116.8 (-0.9)	4.3 (3.2)		-0.5 (-1.1)	1.5 (2.8)	74.1
P,PR,TR,IT,RP	-92.8 (-0.7)	4.2 (3.2)	-41.1 (-0.6)	-0.5 (-1.1)	1.5 (2.9)	74.4
P,PR,TR3,IT3	-62.7 (-0.4)	4.4 (3.1)		-2.6 (-2.7)	3.5 (3.6)	91.4
P,PR,TR3,IT3,RP	-66.3 (-0.5)	4.4 (3.1)	7.5 (0.1)	-2.6 (-2.7)	3.5 (3.6)	91.4
P,PR,TR5,IT5	-130.7 (-0.9)	4.2 (3.1)		--1.0 (1.6)	2.6 (3.8)	85.5
P,PR,TR5,IT5,RP	-132.9 (-0.9)	4.2 (3.1)	5.7 (0.1)	-1.0 (-1.6)	2.6 (3.8)	85.5

Table 5.7 Estimates for catsup segment 5 (14,28,32 oz)
(n=777, nob=8, null log likelihood=-1615.7)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.1)	2.4 (16.3)				936.6
P,PR,RP	-0.0 (-3.1)	2.1 (13.1)	-66.4 (-8.7)			1021.7
P,PR,TR,IT	-0.0 (-1.7)	2.5 (15.9)		0.7 (5.5)	0.8 (6.7)	1050.1
P,PR,TR,IT,RP	-0.0 (-1.7)	2.1 (12.9)	-69.7 (-9.0)	0.6 (4.8)	0.9 (7.4)	1138.5
P,PR,TR3,IT3	-0.0 (-1.2)	2.4 (15.5)		0.9 (7.6)	0.8 (7.8)	1123.8
P,PR,TR3,IT3,RP	-0.0 (1.1)	2.0 (12.1)	-75.9 (-9.6)	0.7 (5.9)	1.1 (9.5)	1227.5
P,PR,TR5,IT5	-0.0 (-0.1)	2.4 (14.9)		1.1 (9.1)	0.9 (7.7)	1148.4
P,PR,TR5,IT5,RP	-0.0 (-0.8)	2.0 (11.9)	-73.8 (-9.3)	1.0 (7.7)	1.1 (9.2)	1243.1

Table 5.8 Estimates for catsup segment 6 (28,32,40 oz)
(n=1620, nob=8, null log likelihood=-3368.7)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-7.9)					1302.8
P,PR,RP	-0.0 (-6.2)		-80.4 (-13.8)			1504.7
P,PR,TR,IT	-0.0 (-6.3)			0.2 (2.9)	0.8 (10.6)	1457.6
P,PR,TR,IT,RP	-0.0 (-6.2)		-81.1 (-13.7)	0.1 (1.7)	0.8 (11.0)	1656.9
P,PR,TR3,IT3	-0.0 (-5.9)			0.3 (4.1)	0.9 (14.4)	1587.8
P,PR,TR3,IT3,RP	-0.0 (-5.7)		-90.9 (-15.2)	0.2 (2.6)	1.0 (16.0)	1834.4
P,PR,TR5,IT5	-0.0 (-5.0)			0.3 (4.1)	0.9 (14.2)	1585.8
P,PR,TR5,IT5,RP	-0.0 (-4.8)		-88.4 (-14.7)	0.2 (2.7)	1.1 (15.4)	1817.7

Table 5.9 Estimates for catsup segment 7 (28,32,64 oz)
(n=496, nob=8, null log likelihood=-1031.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-2.8)					362.5
P,PR,RP	-0.0 (-2.9)		-57.6 (-5.1)			390.2
P,PR,TR,IT	-0.0 (-1.7)			0.6 (4.3)	0.9 (7.3)	454.9
P,PR,TR,IT,RP	-0.0 (-1.8)		-57.7 (-5.1)	0.5 (4.0)	1.0 (7.4)	482.1
P,PR,TR3,IT3	-0.0 (-1.4)			0.3 (2.5)	1.3 (11.2)	538.7
P,PR,TR3,IT3,RP	-0.0 (-1.5)		-72.5 (-6.2)	0.2 (1.8)	1.5 (11.7)	579.2
P,PR,TR5,IT5	-0.0 (-0.7)			0.5 (3.6)	1.3 (10.1)	521.2
P,PR,TR5,IT5,RP	-0.0 (-0.8)		-62.8 (-5.5)	0.4 (2.8)	1.4 (10.5)	552.9

Table 5.10 Estimates for catsup segment 8 (28,32,44 oz)
(n=1740, nob=9, null log likelihood=-3823.2)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-6.7)	2.6 (24.0)				2677.4
P,PR,RP	-0.0 (-6.8)	2.4 (22.0)	-34.5 (-5.6)			2709.2
P,PR,TR,IT	-0.0 (-3.8)	2.6 (23.7)		0.4 (5.5)	0.6 (8.4)	2807.2
P,PR,TR,IT,RP	-0.0 (-3.9)	2.4 (21.7)	-34.6 (-5.5)	0.4 (5.3)	0.7 (8.5)	2838.2
P,PR,TR3,IT3	--0.0 (3.8)	2.7 (24.2)		0.5 (5.7)	1.0 (14.6)	3025.1
P,PR,TR3,IT3,RP	-0.0 (-4.1)	2.5 (21.8)	-45.0 (-7.1)	0.4 (4.7)	1.1 (15.3)	3076.2
P,PR,TR5,IT5	-0.0 (-2.1)	2.7 (23.9)		0.6 (6.9)	1.1 (14.6)	3034.3
P,PR,TR5,IT5,RP	-0.4 (-2.4)	2.5 (21.7)	-41.7 (-6.5)	0.5 (6.1)	1.2 (15.1)	3077.6

Table 5.11 Estimates for catsup segment 9 (32,40,44 oz)
(n=107, nob=7, null log likelihood=-208.2)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.6)	2.9 (6.0)				138.2
P,PR,RP	-0.0 (-3.6)	2.7 (5.4)	-34.0 (-1.2)			139.7
P,PR,TR,IT	-0.0 (-3.3)	3.0 (6.0)		-0.6 (1.7)	1.1 (3.3)	151.8
P,PR,TR,IT,RP	-0.0 (-3.2)	2.8 (5.4)	-29.6 (-1.1)	-0.5 (-1.7)	1.1 (3.2)	152.9
P,PR,TR3,IT3	-0.0 (-2.6)	3.1 (6.1)		0.0 (0.1)	1.0 (3.2)	151.0
P,PR,TR3,IT3,RP	-0.0 (-2.6)	2.9 (5.4)	-49.2 (-1.7)	0.2 (0.6)	1.0 (3.4)	154.0
P,PR,TR5,IT5	-0.0 (-2.8)	3.1 (6.1)		-0.2 (-0.8)	0.9 (3.0)	147.8
P,PR,TR5,IT5,RP	-0.0 (-2.8)	2.9 (5.5)	-40.8 (-1.4)	-0.3 (-0.8)	0.9 (3.1)	149.9

Table 5.12 Estimates for catsup segment 10 (14,28,32,40 oz)
(n=318, nob=9, null log likelihood=-698.7)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-2.8)	2.4 (9.9)				468.1
P,PR,RP	-0.0 (-2.8)	2.3 (9.2)	-47.7 (-3.0)			477.4
P,PR,TR,IT	-0.0 (-1.8)	2.6 (9.8)		0.7 (3.8)	0.7 (4.2)	509.2
P,PR,TR,IT,RP	-0.0 (-1.8)	2.4 (9.3)	-43.8 (-2.7)	0.6 (3.5)	0.8 (4.3)	516.6
P,PR,TR3,IT3	-0.0 (-1.9)	2.5 (9.7)		0.5 (2.9)	0.9 (5.7)	532.4
P,PR,TR3,IT3,RP	-0.0 (-1.9)	2.3 (8.8)	-56.1 (-3.5)	0.4 (2.4)	1.0 (6.1)	544.8
P,PR,TR5,IT5	-0.0 (-1.8)	2.5 (9.6)		0.4 (2.4)	0.7 (4.4)	504.6
P,PR,TR5,IT5,RP	-0.0 (-1.8)	2.3 (8.8)	-51.2 (-3.2)	0.4 (2.0)	0.8 (4.7)	515.0

Table 5.13 Estimates for catsup segment 11 (14,28,32,44 oz)
(n=173, nob=8, null log likelihood=-359.7)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-1.4)	2.8 (7.1)				266.8
P,PR,RP	-0.0 (-1.5)	2.6 (6.4)	-32.3 (-1.9)			270.6
P,PR,TR,IT	-0.0 (-0.7)	2.7 (6.9)		0.1 (0.2)	0.9 (3.3)	278.7
P,PR,TR,IT,RP	-0.0 (-0.7)	2.5 (6.1)	-37.3 (-2.2)	0.1 (0.3)	0.9 (3.5)	283.5
P,PR,TR3,IT3	-0.0 (-0.4)	2.8 (7.0)		0.4 (1.6)	0.8 (3.6)	285.8
P,PR,TR3,IT3,RP	-0.0 (-0.5)	2.5 (6.1)	-41.5 (-2.5)	0.3 (1.3)	0.9 (3.9)	291.9
P,PR,TR5,IT5	-0.0 (0.7)	2.7 (6.9)		-0.1 (-0.2)	0.8 (3.1)	276.8
P,PR,TR5,IT5,RP	-0.0 (-0.8)	2.5 (6.0)	-40.0 (-2.4)	-0.1 (-0.4)	0.9 (3.4)	282.5

Table 5.14 Estimates for catsup segment 12 (28,32,40,44 oz)
(n=1451, nob=10, null log likelihood=-3341.1)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-12.4)					1270.3
P,PR,RP	-0.0 (-12.4)		-72.5 (-10.9)			1393.3
P,PR,TR,IT	-0.0 (-10.1)			0.4 (5.1)	0.9 (11.7)	1477.9
P,PR,TR,IT,RP	-0.0 (-10.1)		-72.9 (-10.7)	0.3 (4.5)	0.9 (12.0)	1597.2
P,PR,TR3,IT3	-0.0 (-9.3)			0.5 (6.4)	0.8 (12.3)	1552.5
P,PR,TR3,IT3,RP	-0.0 (-9.2)		-81.4 (-11.8)	0.4 (5.5)	0.9 (13.4)	1699.7
P,PR,TR5,IT5	-0.0 (-7.7)			0.6 (7.0)	0.9 (12.6)	1567.8
P,PR,TR5,IT5,RP	-0.0 (-7.8)		-77.0 (-11.2)	0.5 (6.2)	0.9 (13.3)	1699.5

Table 5.15 Estimates for catsup segment 13 (28,32,44,64 oz)
(n=610, nob=9, null log likelihood=-1340.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-5.7)	2.4 (14.6)				987.3
P,PR,RP	-0.0 (-5.8)	2.2 (13.4)	-28.9 (-2.7)			994.5
P,PR,TR,IT	-0.0 (-5.4)	2.4 (14.6)		0.0 (0.2)	0.5 (3.8)	1002.8
P,PR,TR,IT,RP	-0.0 (-5.5)	2.3 (13.6)	-29.2 (-2.7)	0.0 (0.1)	0.5 (3.8)	1010.0
P,PR,TR3,IT3	-0.0 (-4.8)	2.4 (14.6)		0.8 (0.6)	0.8 (7.1)	1054.5
P,PR,TR3,IT3,RP	-0.0 (-4.8)	2.3 (13.5)	-35.3 (-3.2)	0.0 (0.4)	0.9 (7.4)	1065.0
P,PR,TR5,IT5	-0.0 (-4.4)	2.4 (14.4)		0.4 (2.8)	0.6 (5.2)	1039.9
P,PR,TR5,IT5,RP	-0.0 (-4.4)	2.3 (13.3)	-32.4 (-3.0)	0.3 (2.7)	0.7 (5.4)	1048.8

Table 5.16 Estimates for catsup segment 14 (28,32,44,64 oz)
(n=343, nob=10, null log likelihood=-789.8)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-4.2)	2.6 (11.3)				467.4
P,PR,RP	-0.0 (-4.2)	2.4 (10.0)	-52.9 (-3.2)			477.9
P,PR,TR,IT	-0.0 (-3.1)	2.6 (11.3)		0.2 (0.9)	0.5 (2.8)	478.1
P,PR,TR,IT,RP	-0.0 (-3.1)	2.4 (10.0)	-53.7 (-3.2)	0.1 (0.8)	0.5 (2.9)	488.7
P,PR,TR3,IT3	-0.0 (-2.6)	2.7 (11.4)		0.1 (0.7)	1.1 (7.3)	530.8
P,PR,TR3,IT3,RP	-0.0 (-2.7)	2.4 (9.9)	-65.2 (-3.9)	0.1 (0.4)	1.2 (7.6)	546.2
P,PR,TR5,IT5	-0.0 (-2.3)	2.6 (11.2)		0.0 (0.4)	1.0 (6.7)	519.9
P,PR,TR5,IT5,RP	-0.0 (-2.4)	2.4 (9.7)	-61.1 (-3.7)	0.0 (0.2)	1.1 (7.0)	533.6

Table 5.17 Estimates for catsup segment 15 (32,40,44,64 oz)
(n=98, nob=7, null log likelihood=-191.0)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.1)	1.7 (3.4)				101.7
P,PR,RP	-0.0 (-3.1)	1.6 (3.1)	-28.1 (-0.9)			102.5
P,PR,TR,IT	-0.0 (-2.7)	1.8 (3.5)		0.7 (2.3)	-0.1 (-0.2)	107.4
P,PR,TR,IT,RP	-0.0 (-2.7)	1.7 (3.2)	-25.7 (-0.8)	0.7 (2.3)	-0.1 (-0.2)	108.0
P,PR,TR3,IT3	-0.0 (-2.3)	2.0 (3.6)		0.6 (1.9)	1.0 (3.4)	131.9
P,PR,TR3,IT3,RP	-0.0 (-2.3)	1.8 (3.3)	-33.8 (-1.0)	0.6 (1.9)	1.0 (3.4)	132.9
P,PR,TR5,IT5	-0.0 (-1.9)	2.1 (3.7)		1.2 (3.1)	0.7 (2.5)	131.1
P,PR,TR5,IT5,RP	-0.0 (-1.9)	2.0 (3.4)	-40.5 (-1.2)	1.2 (3.1)	0.8 (2.5)	132.5

Table 5.18 Estimates for catsup segment 16 (14,28,32,40,44 oz)
(n=238, nob=10, null log likelihood=-548.0)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.8)					319.2
P,PR,RP	-0.0 (-3.8)		-104.9 (-6.6)			369.8
P,PR,TR,IT	-0.0 (-3.6)			0.4 (1.8)	0.3 (1.3)	325.7
P,PR,TR,IT,RP	-0.0 (-3.6)		-104.3 (-6.6)	0.3 (1.5)	0.3 (1.4)	375.6
P,PR,TR3,IT3	-0.0 (-3.2)			0.6 (3.3)	0.5 (2.7)	349.0
P,PR,TR3,IT3,RP	-0.0 (-3.2)		-108.5 (-6.8)	0.6 (3.2)	0.5 (2.9)	402.7
P,PR,TR5,IT5	-0.0 (-3.2)			0.4 (2.3)	0.6 (3.2)	341.0
P,PR,TR5,IT5,RP	-0.0 (-3.1)		-109.0 (-6.9)	0.4 (2.1)	0.7 (3.6)	395.4

Table 5.19 Estimates for catsup segment 17 (14,28,32,40,64 oz)
(n=192, nob=8, null log likelihood=-399.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.5)	2.2 (6.4)				258.1
P,PR,RP	-0.0 (-3.6)	2.1 (6.0)	-55.5 (-2.2)			263.0
P,PR,TR,IT	-0.0 (-3.0)	2.2 (6.4)		0.7 (2.9)	-0.0 (-0.4)	266.9
P,PR,TR,IT,RP	-0.0 (-3.0)	2.1 (6.0)	-61.1 (-2.3)	0.7 (3.0)	-0.1 (-0.4)	272.5
P,PR,TR3,IT3	-0.0 (-2.7)	2.4 (6.8)		0.5 (2.0)	0.6 (2.7)	284.0
P,PR,TR3,IT3,RP	-0.0 (-2.8)	2.3 (6.4)	-62.5 (-2.4)	0.5 (2.1)	0.6 (2.7)	289.8
P,PR,TR5,IT5	-0.0 (-2.1)	2.4 (6.6)		0.6 (2.2)	0.9 (3.6)	297.1
P,PR,TR5,IT5,RP	-0.0 (-2.3)	2.3 (6.2)	-63.0 (-2.4)	0.6 (2.3)	0.9 (3.6)	302.8

Table 5.20 Estimates for catsup segment 18 (28,32,40,44,64 oz)
(n=1303, nob=11, null log likelihood=-3124.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-10.8)					1514.5
P,PR,RP	-0.0 (-10.8)		-78.8 (-10.0)			1618.4
P,PR,TR,IT	-0.0 (-9.7)			0.3 (3.6)	0.4 (5.1)	1562.7
P,PR,TR,IT,RP	-0.0 (-9.7)		-80.0 (-10.1)	0.2 (3.2)	0.4 (5.4)	1667.5
P,PR,TR3,IT3	-0.0 (-9.3)			0.3 (4.4)	0.6 (9.2)	1673.6
P,PR,TR3,IT3,RP	-0.0 (-9.3)		-85.5 (-10.7)	0.3 (3.6)	0.7 (10.2)	1792.6
P,PR,TR5,IT5	-0.0 (-8.6)			0.4 (5.2)	0.7 (9.3)	1674.9
P,PR,TR5,IT5,RP	-0.0 (-8.6)		-83.4 (-10.4)	0.4 (4.6)	0.7 (10.0)	1788.4

Table 5.21 Estimates for catsup segment 19 (14,28,32,40,44,64 oz) (n=318, nob=11, null log likelihood=-762.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-5.1)	1.9 (8.3)				487.9
P,PR,RP	-0.0 (-5.1)	1.8 (7.5)	-36.7 (-1.9)			491.8
P,PR,TR,IT	-0.0 (-4.3)	1.9 (8.3)		0.5 (3.0)	0.1 (0.5)	497.2
P,PR,TR,IT,RP	-0.0 (-4.3)	1.8 (7.6)	-34.8 (-1.8)	0.5 (2.9)	0.0 (0.0)	500.6
P,PR,TR3,IT3	-0.0 (-4.1)	2.1 (8.5)		0.6 (3.2)	0.7 (4.6)	545.8
P,PR,TR3,IT3,RP	-0.0 (-4.1)	1.9 (7.7)	-39.3 (-2.1)	0.5 (3.1)	0.7 (4.7)	550.1
P,PR,TR5,IT5	-0.0 (-3.7)	2.0 (8.4)		0.6 (3.3)	0.8 (4.8)	544.0
P,PR,TR5,IT5,RP	-0.0 (-3.7)	1.9 (7.6)	-39.2 (-2.0)	0.6 (3.2)	0.8 (4.90	548.2

Table 5.22 Estimates for catsup segment 20 (1/2 items in initial period) (n=709, nob=9, null log likelihood=-1557.8)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-71.1 (-9.8)					392.9
P,PR,RP	-67.0 (-9.1)		-38.2 (-4.8)			416.5
P,PR,TR,IT	-76.9 (-9.7)			0.6 (5.6)	1.9 (18.1)	904.4
P,PR,TR,IT,RP	-73.4 (-9.1)		-38.4 (-4.6)	0.6 (5.3)	1.9 (18.2)	925.8
P,PR,TR3,IT3	-74.0 (-8.8)			0.8 (7.10	2.1 (19.8)	1183.8
P,PR,TR3,IT3,RP	-69.7 (-8.1)		-53.2 (-6.1)	0.7 (6.2)	2.2 (20.0)	1223.2
P,PR,TR5,IT5	-74.9 (-8.9)			0.9 (7.6)	2.2 (19.9)	1206.8
P,PR,TR5,IT5,RP	-71.4 (-8.3)		-47.0 (-5.5)	0.8 (7.1)	2.3 (20.2)	1237.9

Table 5.23 Estimates for catsup segment 21 (3 items in initial period) (n=5755, nob=12, null log likelihood=-14300.6)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-17.2)					5663.3
P,PR,RP	-0.0 (-17.1)		-80.5 (-25.9)			6366.6
P,PR,TR,IT	-0.0 (-9.5)			0.7 (17.9)	0.8 (21.1)	6703.7
P,PR,TR,IT,RP	-0.0 (-9.7)		-80.0 (-25.1)	0.6 (16.2)	0.8 (21.8)	7364.2
P,PR,TR3,IT3	-0.0 (-9.6)			0.6 (16.5)	1.1 (33.0)	7655.9
P,PR,TR3,IT3,RP	-0.0 (-9.7)		-91.3 (-28.2)	0.5 (13.5)	1.3 (35.8)	8504.7
P,PR,TR5,IT5	-0.0 (-5.6)			0.8 (19.0)	1.2 (33.7)	7831.7
P,PR,TR5,IT5,RP	-0.0 (-5.8)		-87.2 (-26.7)	0.7 (16.1)	1.4 (35.8)	8595.5

Table 5.24 Estimates for catsup segment 22 (4 items in initial period)
(n=2531, nob=12, null log likelihood=-6289.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-11.5)					2461.7
P,PR,RP	-0.0 (-11.3)		-86.6 (-18.6)			2837.9
P,PR,TR,IT	-0.0 (-5.8)			0.5 (7.6)	0.7 (13.3)	2757.9
P,PR,TR,IT,RP	-0.0 (-5.8)		-86.9 (-18.3)	0.4 (6.8)	0.8 (13.6)	3126.1
P,PR,TR3,IT3	-0.0 (-7.5)			0.5 (8.8)	0.9 (18.0)	3005.1
P,PR,TR3,IT3,RP	-0.0 (-7.3)		-98.0 (-20.1)	0.4 (6.7)	1.1 (20.4)	3456.4
P,PR,TR5,IT5	-0.0 (-5.3)			0.5 (9.1)	1.0 (18.8)	3044.7
P,PR,TR5,IT5,RP	-0.0 (-5.3)		-92.1 (-19.1)	0.4 (7.3)	1.1 (20.2)	3448.8

Table 5.25 Yogurt segments

Segment	Description	Number of Observations	Number of Items
	Sizes purchased		
1	6 oz	314	5
2	8 oz - Market 1	243	4
3	8 oz - Market 2	250	5
	Number of Items in Initial Period		
4	1,2 items-Market 1	92	5
5	1,2 items-Market 2	179	5
6	>2 items -Market 1	84	5
7	>2 items -Market 2	35	4

Table 5.26 Estimates for yogurt segment 1 (6 oz)
(n=314, nob=5, null log likelihood=-505.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-17.2 (-1.9)	2.2 (7.0)				247.9
P,PR,RP	-41.7 (-3.5)	2.2 (7.1)	27.5 (3.2)			258.5
P,PR,TR,IT	-13.8 (-1.4)	2.3 (6.6)		0.5 (2.3)	2.1 (11.1)	424.3
P,PR,TR,IT,RP	-34.3 (-2.6)	2.3 (6.6)	22.7 (2.3)	0.4 (1.9)	2.0 (11.0)	429.8
P,PR,TR3,IT3	-23.3 (-1.9)	2.6 (6.3)		0.9 (3.3)	2.6 (12.2)	573.6
P,PR,TR3,IT3,RP	-36.0 (-2.2)	2.6 (6.3)	13.5 (1.1)	0.9 (3.4)	2.5 (12.0)	574.9
P,PR,TR5,IT5	-25.1 (-2.1)	2.5 (6.0)		0.9 (3.2)	2.5 (11.4)	556.8
P,PR,TR5,IT5,RP	-41.8 (-2.6)	2.6 (6.1)	17.6 (1.6)	0.9 (3.2)	2.5 (11.3)	559.2

Table 5.27 Estimates for yogurt segment 2 (8 oz in market 1)
(n=243, nob=4, null log likelihood=-336.9)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-83.2 (-4.7)	1.4 (4.0)				260.2
P,PR,RP	-115.3 (-5.0)	1.4 (4.1)	38.8 (2.3)			265.5
P,PR,TR,IT	-57.7 (-2.9)	1.8 (4.3)		1.3 (3.5)	1.4 (4.7)	328.7
P,PR,TR,IT,RP	-70.4 (-2.7)	1.8 (4.4)	14.8 (0.8)	1.2 (3.4)	1.4 (4.5)	329.3
P,PR,TR3,IT3	-76.5 (-3.7)	2.0 (4.7)		0.8 (2.7)	1.8 (6.7)	373.5
P,PR,TR3,IT3,RP	-71.0 (-2.6)	2.0 (4.7)	-6.4 (-0.3)	0.7 (2.6)	1.8 (6.4)	373.6
P,PR,TR5,IT5	-76.9 (-3.7)	2.1 (4.7)		1.3 (3.8)	1.7 (5.8)	376.4
P,PR,TR5,IT5,RP	-77.6 (-2.9)	2.1 (4.6)	0.9 (0.0)	1.3 (3.8)	1.7 (5.8)	376.4

Table 5.28 Estimates for yogurt segment 3 (6 oz in market 2)
(n=250, nob=5, null log likelihood=-402.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-18.7 (-1.6)	1.4 (3.4)				251.2
P,PR,RP	-32.2 (-2.4)	1.5 (3.5)	21.2 (2.0)			255.4
P,PR,TR,IT	-29.0 (-2.2)	1.2 (2.6)		-0.2 (-0.8)	2.2 (10.2)	386.9
P,PR,TR,IT,RP	-44.9 (-2.8)	1.2 (2.6)	21.6 (1.9)	-0.3 (-1.0)	2.2 (10.2)	390.4
P,PR,TR3,IT3	-33.5 (-2.0)	1.4 (2.5)		0.9 (3.1)	2.4 (10.7)	494.8
P,PR,TR3,IT3,RP	-41.6 (-2.0)	1.4 (2.5)	11.0 (0.8)	0.9 (3.1)	2.4 (10.6)	495.4
P,PR,TR5,IT5	-37.6 (-2.2)	1.3 (2.3)		0.7 (2.1)	2.5 (10.6)	481.4
P,PR,TR5,IT5,RP	-45.5 (-2.3)	1.4 (2.4)	13.1 (0.9)	0.7 (2.1)	2.5 (10.5)	482.2

Table 5.29 Estimates for yogurt segment 4 (1/2 items in inital period-market 1) (n=92, nob=5, null log likelihood=-148.1)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-154.0 (-4.4)					169.0
P,PR,RP	-233.5 (-4.8)		98.5 (2.7)			176.1
P,PR,TR,IT	-153.7 (-3.1)			1.2 (1.6)	3.4 (4.5)	220.9
P,PR,TR,IT,RP	-218.5 (-3.4)		73.8 (1.8)	1.2 (1.6)	3.3 (4.3)	224.1
P,PR,TR3,IT3	-141.9 (-3.2)			0.4 (0.6)	2.4 (4.4)	206.8
P,PR,TR3,IT3,RP	-164.0 (-2.9)		27.9 (0.7)	0.4 (0.7)	2.3 (4.0)	207.3
P,PR,TR5,IT5	-117.0 (-2.9)			1.8 (2.8)	1.7 (3.3)	208.7
P,PR,TR5,IT5,RP	-151.8 (-2.8)		39.7 (1.0)	1.9 (2.8)	1.5 (2.8)	209.6

Table 5.30 Estimates for yogurt segment 5 (1/2 items in inital period - market 2) (n=179, nob=5, null log likelihood=-288.1)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-27.3 (-3.8)					60.5
P,PR,RP	-28.2 (-3.2)		1.5 (0.2)			60.5
P,PR,TR,IT	-49.6 (-4.0)			-0.8 (-1.5)	5.2 (8.9)	428.3
P,PR,TR,IT,RP	-43.4 (-2.8)		-10.2 (-0.6)	-0.9 (-1.5)	5.2 (8.9)	428.7
P,PR,TR3,IT3	-64.6 (-4.6)			0.8 (1.3)	4.7 (8.9)	481.8
P,PR,TR3,IT3,RP	-44.7 (-2.3)		-27.8 (-1.5)	0.8 (1.2)	4.9 (8.6)	484.3
P,PR,TR5,IT5	-60.2 (-4.3)			0.5 (0.8)	5.1 (8.4)	478.9
P,PR,TR5,IT5,RP	-42.6 (-2.2)		-24.6 (-1.3)	0.4 (0.6)	5.3 (8.0)	480.7

Table 5.31 Estimates for segment 6 (>2 items in initial period - market 1) (n=84, nob=5, null log likelihood=-135.2)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-28.6 (-1.5)					37.1
P,PR,RP	-24.9 (-1.0)		-4.4 (-0.2)			37.1
P,PR,TR,IT	-27.3 (-1.4)			1.6 (3.2)	-0.1 (-0.2)	50.9
P,PR,TR,IT,RP	-26.5 (-1.0)		-0.9 (-0.0)	1.6 (3.2)	-0.1 (-0.2)	50.9
P,PR,TR3,IT3	-45.5 (-2.2)			0.7 (1.9)	1.1 (3.2)	75.3
P,PR,TR3,IT3,RP	-44.0 (-1.5)		-1.8 (-0.1)	0.7 (1.9)	1.1 (3.2)	75.3
P,PR,TR5,IT5	-34.1 (-1.6)			0.9 (2.0)	1.1 (2.9)	68.5
P,PR,TR5,IT5,RP	-34.0 (-1.2)		-0.2 (-0.1)	0.9 (2.0)	1.1 (2.9)	68.5

Table 5.32 Estimates for yogurt segment 7 (>2 items in initial period - market 2) (n=35, nob=4, null log likelihood=-48.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-11.7 (-0.7)					17.9
P,PR,RP	-6.3 (-0.3)		-7.6 (-0.3)			18.0
P,PR,TR,IT**						
P,PR,TR,IT,RP**						
P,PR,TR3,IT3	-31.1 (-1.5)			1.4 (2.2)	1.1 (2.3)	31.8
P,PR,TR3,IT3,RP	-14.0 (-0.5)		-32.4 (-1.2)	1.5 (2.2)	1.3 (2.5)	33.4
P,PR,TR5,IT5	-32.5 (-1.7)			1.9 (2.3)	0.7 (1.4)	28.6
P,PR,TR5,IT5,RP	-14.6 (-0.6)		-31.5 (-1.2)	2.0 (2.4)	0.8 (1.7)	30.3

** iterative procedure did not converge for this model

Table 5.33 Dishwashing detergent segments

Segment	Description	Number of Observations	Number of Items
	Sizes purchased		
1	12 oz	105	5
2	12,22 oz	585	13
3	22,32 oz	90	14
4	12,22,32 oz	706	21
5	22,32,48 oz	399	22
6	12,22,32,48 oz	41	16
	Number of items in initial period		
7	1 or 2 items	1317	23
8	3 items	947	26
9	4 or 5 items	845	26

Table 5.34 Estimates for dishwashing detergent segment 1 (12 oz) (n=105, nob=5, null log likelihood=-169.0)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-6.9 (-0.2)					49.1
P,PR,RP	1.7 (0.0)		-22.1 (-0.4)			49.3
P,PR,TR,IT	-60.4 (-1.2)			0.0 (0.0)	4.0 (4.4)	168.2
P,PR,TR,IT,RP	-46.7 (-0.8)		-37.8 (-0.6)	0.1 (0.1)	4.0 (4.4)	168.6
P,PR,TR3,IT3	-27.4 (-0.5)			0.8 (1.7)	2.2 (6.9)	164.1
P,PR,TR3,IT3,RP	0.0 (0.0)		-70.4 (-1.0)	0.8 (1.8)	2.3 (6.9)	165.2
P,PR,TR5,IT5	-60.9 (-1.1)			0.7 (1.3)	2.8 (6.5)	174.8
P,PR,TR5,IT5,RP	-31.7 (-0.5)		-73.9 (-1.1)	0.7 (1.3)	2.9 (6.5)	176.0

Table 5.35 Estimates for dishwashing detergent segment 2 (12,22 oz) (n=585, nob=13, null log likelihood=-1500.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-4.1)	0.5 (2.1)				316.1
P,PR,RP	-0.0 (-4.1)	0.5 (2.1)	4.1 (0.4)			316.3
P,PR,TR,IT	-0.0 (-3.1)	0.6 (2.4)		0.2 (1.3)	1.9 (18.7)	759.5
P,PR,TR,IT,RP	-0.0 (-3.1)	0.6 (2.4)	2.5 (0.2)	0.2 (1.3)	1.9 (18.7)	759.5
P,PR,TR3,IT3	-0.0 (-3.0)	0.6 (2.5)		0.2 (2.1)	1.9 (19.5)	835.8
P,PR,TR3,IT3,RP	-0.0 (-3.0)	0.6 (2.4)	-3.2 (-0.3)	0.3 (2.1)	1.9 (19.5)	835.9
P,PR,TR5,IT5	-0.0 (-2.3)	0.7 (2.9)		0.4 (3.0)	2.2 (20.4)	948.1
P,PR,TR5,IT5,RP	-0.0 (-2.3)	0.7 (2.8)	-2.4 (-0.2)	0.4 (3.0)	2.2 (20.4)	948.2

Table 5.36 Estimates for dishwashing detergent segment 3 (22,32 oz) (n=90, nob=14, null log likelihood=-237.5)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-55.0 (-2.4)					44.3
P,PR,RP	-71.2 (-2.5)		23.3 (1.0)			45.4
P,PR,TR,IT	-61.3 (-2.4)			0.4 (1.4)	2.9 (9.2)	162.4
P,PR,TR,IT,RP	-77.9 (-2.4)		22.8 (0.9)	0.4 (1.4)	2.8 (9.2)	163.1
P,PR,TR3,IT3	-46.1 (-1.8)			0.3 (0.9)	2.2 (8.8)	127.0
P,PR,TR3,IT3,RP	-63.6 (-2.0)		23.0 (0.9)	0.3 (0.9)	2.2 (8.8)	127.8
P,PR,TR5,IT5	-52.9 (-2.1)			0.3 (0.8)	2.5 (9.3)	150.2
P,PR,TR5,IT5,RP	-66.6 (-2.1)		17.9 (0.7)	0.2 (0.8)	2.5 (9.2)	150.7

Table 5.37 Estimates for dishwashing detergent segment 4 (12,22,32 oz) (n=706, nob=21, null log likelihood=-2149.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.8)	0.5 (2.9)				453.6
P,PR,RP	-0.0 (-3.9)	0.4 (2.2)	-21.4 (-2.6)			460.2
P,PR,TR,IT	-0.0 (-3.1)	0.4 (2.4)		-0.3 (-2.3)	1.6 (18.4)	789.8
P,PR,TR,IT,RP	-0.0 (-3.1)	0.3 (1.9)	-22.1 (-2.5)	-0.2 (-2.0)	1.6 (18.4)	796.3
P,PR,TR3,IT3	-0.0 (-2.7)	0.4 (2.6)		0.0 (0.4)	1.6 (19.7)	844.6
P,PR,TR3,IT3,RP	-0.0 (-2.7)	0.3 (1.9)	-28.6 (-3.3)	0.0 (0.7)	1.7 (20.0)	855.5
P,PR,TR5,IT5	-0.0 (-2.1)	0.5 (2.9)		0.1 (1.0)	1.8 (20.8)	921.6
P,PR,TR5,IT5,RP	-0.0 (-2.1)	0.4 (2.2)	-28.6 (-3.2)	0.2 (1.4)	1.8 (20.8)	932.2

Table 5.38 Estimates for dishwashing detergent segment 5 (22,32,48 oz) (n=399, nob=22, null log likelihood=-1233.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-4.3)					298.1
P,PR,RP	-0.0 (-4.3)		-33.8 (-3.4)			309.9
P,PR,TR,IT	-0.0 (-3.6)			0.1 (0.4)	2.0 (16.5)	598.7
P,PR,TR,IT,RP	-0.0 (-3.6)		-34.5 (-3.4)	0.0 (0.3)	2.0 (16.5)	610.6
P,PR,TR3,IT3	-0.0 (-3.7)			0.9 (6.8)		344.7
P,PR,TR3,IT3,RP	-0.0 (-3.7)		-35.0 (-3.4)	0.9 (6.8)		356.9
P,PR,TR5,IT5	-0.0 (-3.0)			0.3 (2.1)	2.2 (18.5)	712.0
P,PR,TR5,IT5,RP	-0.0 (-3.0)		-42.0 (-3.9)	0.3 (2.1)	2.2 (18.6)	727.8

Table 5.39 Estimates for dishwashing detergent segment 6 (12,22,32,48 oz) (n=41, nob=16, null log likelihood=-113.7)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-78.7 (-0.9)					18.8
P,PR,RP	-47.2 (-0.5)		-38.5 (-0.7)			19.2
P,PR,TR,IT	-75.5 (-0.8)			-0.3 (-0.5)	1.2 (3.1)	28.4
P,PR,TR,IT,RP	-26.1 (-0.2)		-61.1 (-1.0)	-0.3 (-0.5)	1.3 (3.2)	29.6
P,PR,TR3,IT3	-21.0 (-0.2)			-0.4 (-1.0)	1.5 (4.3)	35.7
P,PR,TR3,IT3,RP	38.9 (0.4)		-65.0 (-1.2)	-0.5 (-1.1)	1.6 (4.3)	37.1
P,PR,TR5,IT5	-44.7 (-0.5)			-0.1 (-0.3)	1.7 (4.7)	41.7
P,PR,TR5,IT5,RP	21.0 (0.2)		-71.8 (-1.3)	-0.2 (-0.3)	1.8 (4.8)	43.3

Table 5.40 Estimates for dishwashing detergent segment 7 (1/2 items in inital period) (n=1317, nob=23, null log likelihood=-4129.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-5.4)					757.7
P,PR,RP	-0.0 (-5.3)		-16.3 (-2.6)			764.3
P,PR,TR,IT	-0.0 (-3.4)			1.5 (20.1)		1210.5
P,PR,TR,IT,RP	-0.0 (-3.4)		-24.8 (-3.7)	1.5 (21.0)		1224.4
P,PR,TR3,IT3	-0.0 (-3.3)			2.0 (26.1)		1474.0
P,PR,TR3,IT3,RP	-0.0 (-3.3)		-29.5 (-4.3)	1.9 (26.4)		1492.7
P,PR,TR5,IT5	-0.0 (-2.4)			2.0 (26.0)		1535.0
P,PR,TR5,IT5,RP	-0.0 (-2.4)		-29.1 (-4.2)	2.0 (26.2)		1553.0

Table 5.41 Estimates for dishwashing detergent segment 8 (3 items in initial period) (n=947, nob=26, null log likelihood=-3085.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-6.7)					640.7
P,PR,RP	-0.0 (-6.8)		-27.4 (-3.8)			655.1
P,PR,TR,IT	-0.0 (-5.6)			1.1 (12.6)		811.0
P,PR,TR,IT,RP	-0.0 (-5.6)		-33.6 (-4.5)	1.1 (12.8)		831.4
P,PR,TR3,IT3	-0.0 (-5.3)			1.4 (17.7)		968.2
P,PR,TR3,IT3,RP	-0.0 (-5.3)		-31.9 (-4.2)	1.4 (17.8)		986.3
P,PR,TR5,IT5	-0.0 (-4.6)			1.6 (18.1)		1019.0
P,PR,TR5,IT5,RP	-0.0 (-4.6)		-31.3 (-4.2)	1.6 (18.2)		1036.4

Table 5.42 Estimates for dishwashing detergent segment 9 (4/5 items in initial period)

(n=845, nob=26, null log likelihood=-2753.1)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-0.0 (-3.8)					541.2
P,PR,RP	-0.0 (-3.8)		-35.9 (-5.0)			566.1
P,PR,TR,IT	-0.0 (-3.0)			0.2 (1.5)	1.3 (16.7)	837.6
P,PR,TR,IT,RP	-0.0 (-3.0)		-36.6 (-5.0)	0.2 (1.6)	1.3 (16.7)	862.9
P,PR,TR3,IT3	-0.0 (-2.7)			0.2 (2.1)	1.4 (18.1)	876.9
P,PR,TR3,IT3,RP	-0.0 (-2.7)		-41.3 (-5.6)	0.2 (2.5)	1.4 (18.2)	908.5
P,PR,TR5,IT5	-0.0 (-2.3)			0.2 (2.3)	1.5 (19.2)	946.8
P,PR,TR5,IT5,RP	-0.0 (-2.2)		-41.5 (-5.6)	0.3 (2.7)	1.5 (19.3)	978.5

Table 5.43 Summary of best fitting models for segment-wise analysis for catsup

#	Segment	P	PR	RP	TR	IT	TR3	IT3	TR5	IT5
1	32	*	*	x			*	*		
2	28,32	*								*
3	32,40	*	x	x	x	*				
4	32,44	x	*	x	+	*				
5	14,28,32	x	*	*					*	*
6	28,32,40	*		*			*	*		
7	28,32,64	x		*			x	*		
8	28,32,44	*	*	*					*	*
9	32,40,44	*	*	x			x	*		
10	14,28,32,40	x	*	*			*	*		
11	14,28,32,44	x	*	*			x	*		
12	28,32,40,44	*		*			*	*		
13	28,32,40,64	*	*	*			x	*		
14	28,32,44,64	*	*	*			x	*		
15	32,40,44,64	*	*	x			x	*		
16	14,28,32,40,44	*		*			*	*		
17	14,28,32,40,64	*	*	*					*	*
18	28,32,40,44,64	*		*			*	*		
19	All sizes	*	*	*					*	*
20	1 or 2 items	*		*					*	*
21	3 items	*		*					*	*
22	4 items	*		*			*	*		

Note. The symbol * indicates that the variable was included in the best fitting model for the segment, and was statistically significant at the 0.05 level. The symbol x indicates that the variable was included in the best fitting model, but was not statistically significant at the .05 level. The symbol + indicates that the variable was significant but of the opposite sign from that predicted.

Table 5.44 Summary of best fitting models for segment-wise analysis for yogurt

#	Segment	P	PR	RP	TR	IT	TR3	IT3	TR5	IT5
1	6 oz	*	*	x			*	*		
2	8 oz Market 1	*	*	x					*	*
3	8 oz Market 2	*	*	x			*	*		
4	1/2 items in inital period, market 1	*		x	x	*				
5	1/2 items in initial period, market 2	*	x				x	*		
6	> 2 items in initial period, market 1	x		x			x	*		
7	> 2 items in initial period, market 2	x		x			*	*		

Table 5.45 Summary of best fitting models for segment-wise analysis for dishwashing detergent

#	Segment	P	PR	RP	TR	IT	TR3	IT3	TR5	IT5
1	12 oz	x		x					x	*
2	12,22 oz	*	*	*					*	*
3	22,32 oz	*		x	x	*				
4	12,22,32 oz	*	*	*					x	*
5	22,32,48 oz	*		*					*	*
6	12,22,32,48 oz	x		x					x	*
7	1/2 items in initial period	*		*					*	
8	3 items in initial period	*		*					*	
9	4/5 items in initial period	*		*					*	*

Table 5.46 Estimates for aggregated dataset for catsup
(n=740, nob=9, null log likelihood = -1625.9)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-93.5 (-10.8)	1.7 (11.7)				843.7
P,PR,RP	-105.8 (-10.6)	1.7 (11.7)	19.9 (2.5)			850.0
P,PR,TR	-88.0 (-10.1)	1.7 (11.5)		0.5 (4.1)		861.6
P,PR,IT	-93.5 (-10.3)	1.8 (11.7)			1.6 (15.1)	1088.3
P,PR,TR,IT	-90.9 (-9.9)	1.8 (11.6)		0.2 (1.6)	1.6 (14.6)	1091.0
P,PR,RP,TR,IT	-101.0 (-9.6)	1.8 (11.7)	16.5 (2.0)	0.2 (1.6)	1.6 (14.5)	1095.1
P,PR,TR3	-82.9 (-9.3)	1.8 (11.6)		1.0 (10.1)		950.1
P,PR,IT3	-97.0 (-10.1)	1.9 (11.5)			1.9 (19.2)	1246.1
P,PR,TR3,IT3	-90.1 (-9.2)	1.9 (11.5)		0.5 (4.6)	1.7 (17.0)	1267.8
P,PR,RP,TR3,IT3	-87.0 (-7.8)	1.9 (11.5)	-5.0 (-0.6)	0.5 (4.6)	1.7 (17.0)	1268.2
P,PR,TR5	-83.6 (-9.4)	1.8 (11.6)		1.0 (9.4)		937.7
P,PR,IT5	-100.0 (-10.4)	1.9 (11.5)			2.0 (19.1)	1271.3
P,PR,TR5,IT5	-93.6 (-9.6)	1.9 (11.4)		0.5 (4.4)	1.9 (17.4)	1290.8
P,PR,RP,TR5,IT5	-95.9 (-8.6)	1.9 (11.4)	3.6 (0.4)	0.5 (4.4)	1.9 (17.2)	1291.0

Table 5.47 Estimates for aggregated dataset for catsup with refined measures

Model	P	PR	RP	Price based	Brand based	Size based	χ^2
P,PR,TR,BD,SZ	-93.2 (-10.1)	1.9 (11.8)		0.6 (5.3)	1.7 (10.4)	1.4 (10.2)	1128.9
P,PR,RP,TR,BD,SZ	-104.3 (-9.8)	1.9 (11.9)	17.8 (2.2)	0.6 (5.3)	1.6 (10.3)	1.4 (10.3)	1133.5
P,PR,TR3,BD3,SZ3	-95.4 (-10.0)	1.9 (11.6)		0.3 (2.5)	1.6 (10.9)	1.5 (13.4)	1232.5
P,PR,RP, TR3,BD3,SZ3	-94.6 (-8.6)	1.9 (11.6)	-1.2 (-0.1)	0.3 (2.5)	1.6 (10.7)	1.5 (13.4)	1232.5
P,PR,TR5,BD5,SZ5	-100.3 (-10.6)	1.9 (11.6)		0.3 (3.0)	1.8 (11.1)	1.7 (13.4)	1251.4
P,PR,RP, TR5,BD5,SZ5	-105.0 (-9.6)	1.9 (11.6)	7.3 (0.9)	0.3 (3.0)	1.8 (11.0)	1.7 (13.4)	1252.1
P,PR,RP3	-100.9 (-10.0)	1.7 (11.7)	13.3 (1.5)				845.9
P,PR,RP3,IT3	-83.7 (-7.5)	1.9 (11.5)	-23.1 (-2.3)		1.9 (19.2)		1251.6
P,PR,TR3,IT3	-90.1 (-9.2)	1.9 (11.5)		0.5 (4.6)	1.7 (17.0)		1267.8
P,PR,RP3,TR3,IT3	-78.2 (-6.9)	1.9 (11.4)	-21.0 (-2.1)	0.5 (4.5)	1.8 (17.0)		1272.3
P,PR,RP3,TR3, BD3,SZ3	-80.6 (-7.2)	1.9 (11.6)	-14.6 (-1.5)	0.5 (4.3)	1.6 (10.7)	1.4 (11.6)	1247.2

Table 5.48 Estimated parameters for aggregated dataset for yogurt - (Market 1) (n=218, nob=7, null log likelihood=-424.2)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-53.0 (-3.9)	1.2 (3.8)				289.1
P,PR,RP	-66.6 (-3.7)	1.3 (3.9)	17.0 (1.2)			290.4
P,PR,TR	-39.2 (-2.7)	1.2 (3.3)		2.1 (7.8)		361.8
P,PR,IT	-47.6 (-3.3)	1.5 (4.0)			2.0 (8.4)	369.4
P,PR,TR,IT	-38.2 (-2.5)	1.4 (3.7)		1.4 (4.8)	1.5 (5.6)	394.1
P,PR,RP,TR,IT	-39.9 (-2.0)	1.4 (3.7)	2.2 (0.1)	1.4 (4.8)	1.4 (5.5)	394.1
P,PR,TR3	-2.9 (-42.5)	1.4 (3.7)		1.9 (8.4)		370.6
P,PR,IT3	-64.5 (-4.4)	1.6 (4.0)			2.2 (10.9)	431.4
P,PR,TR3,IT3	-59.7 (-4.0)	1.6 (3.9)		0.8 (2.9)	1.8 (7.8)	440.0
P,PR,RP,TR3,IT3	-52.1 (-2.5)	1.6 (3.8)	-9.5 (-0.5)	0.8 (2.9)	1.9 (7.8)	440.2
P,PR,TR5	-40.1 (-2.7)	1.3 (3.6)		2.2 (8.6)		379.5
P,PR,IT5	-58.6 (-3.8)	1.6 (4.1)			2.3 (10.2)	419.8
P,PR,TR5,IT5	-52.2 (-3.3)	1.6 (3.9)		1.1 (3.7)	1.8 (6.9)	433.6
P,PR,RP,TR5,IT5	-50.0 (-2.4)	1.6 (3.9)	-2.8 (-0.2)	1.1 (3.6)	1.8 (6.8)	433.7

Table 5.49 Estimated parameters for aggregated dataset for yogurt (Market 1) with refined meaures

Model	P	PR	RP	Price based	Brand based	Size based	χ^2
P,PR,TR,BD,SZ	-40.5 (-2.7)	1.4 (3.7)		1.3 (4.5)	1.2 (4.0)	0.9 (1.7)	393.6
P,PR,RP,TR,BD,SZ	-42.9 (-2.1)	1.4 (3.7)	3.0 (0.2)	1.3 (4.5)	1.2 (4.0)	0.9 (1.7)	393.6
P,PR,TR3,BD3,SZ3	-64.9 (-4.4)	1.5 (3.7)		0.7 (2.4)	1.6 (6.5)	0.9 (2.0)	438.8
P,PR,RP, TR3,BD3,SZ3	-60.4 (-2.8)	1.5 (3.7)	-5.5 (-0.3)	0.6 (2.4)	1.6 (6.4)	0.9 (1.9)	438.9
P,PR,TR5,BD5,SZ5	-54.6 (-3.5)	1.6 (3.9)		1.0 (3.1)	1.7 (6.0)	0.6 (1.2)	430.4
P,PR,RP, TR5,BD5,SZ5	-52.3 (-2.5)	1.6 (3.8)	-2.8 (-0.2)	1.0 (3.1)	1.7 (6.0)	0.6 (1.2)	430.4
P,PR,RP3	-73.6 (-3.9)	1.2 (3.8)	25.5 (1.6)				291.5
P,PR,RP3,IT3	-56.6 (-2.5)	1.6 (4.0)	-9.5 (-0.5)		2.2 (10.9)		431.6
P,PR,TR3,RP3	-59.7 (-4.0)	1.6 (3.9)		0.8 (2.9)	1.8 (7.8)		439.9
P,PR,RP3,TR3,IT3	-58.1 (-2.6)	1.6 (3.9)	-2.0 (-0.1)	0.8 (2.9)	1.8 (7.7)		439.9
P,PR,RP3,TR3, BD3,SZ3	-65.2 (-2.9)	1.5 (3.7)	0.3 (0.0)	0.7 (2.4)	1.6 (6.3)	0.9 (2.0)	438.8

Table 5.50 Estimates for aggregated dataset for yogurt - (Market 2)
(n=243, nob=6, null log likelihood =-435.4)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-37.4 (-3.4)	1.1 (2.3)				273.2
P,PR,RP	-43.3 (-3.3)	1.1 (2.3)	8.3 (0.8)			273.8
P,PR,TR	-31.1 (-2.7)	1.0 (2.0)		1.5 (6.1)		316.6
P,PR,IT	-45.0 (-3.1)	1.3 (2.1)			3.8 (12.8)	614.0
P,PR,TR,IT	-44.7 (-3.1)	1.3 (2.0)		0.4 (1.0)	3.7 (12.3)	615.0
P,PR,RP,TR,IT	-53.9 (-2.6)	1.3 (2.0)	10.0 (0.6)	0.3 (0.9)	3.7 (12.2)	615.3
P,PR,TR3	-49.3 (-3.9)	1.3 (2.6)		2.6 (10.7)		450.2
P,PR,IT3	-56.1 (-3.6)	1.2 (1.7)			3.6 (13.0)	642.5
P,PR,TR3,IT3	-55.4 (-3.5)	1.3 (1.9)		0.9 (2.5)	3.2 (10.6)	648.5
P,PR,RP,TR3,IT3	-44.4 (-2.0)	1.3 (1.9)	-11.2 (-0.7)	0.8 (2.3)	3.2 (10.6)	648.9
P,PR,TR5	-47.1 (-3.7)	1.5 (2.7)		2.6 (10.1)		442.6
P,PR,IT5	-53.7 (-3.4)	1.3 (1.9)			3.6 (12.7)	642.2
P,PR,TR5,IT5	-53.2 (-3.4)	1.4 (2.0)		0.6 (1.5)	3.4 (10.3)	644.4
P,PR,RP,TR5,IT5	-43.7 (-2.0)	1.4 (2.0)	-10.3 (-0.6)	0.5 (1.4)	3.4 (10.3)	644.8

Table 5.51 Estimates for aggregated dataset for yogurt (Market 2) with refined measures

Model	P	PR	RP	Price based	Brand based	Size based	χ^2
P,PR,TR,BD,SZ	-60.1 (-3.8)	1.4 (2.1)		0.1 (0.3)	2.6 (6.6)	2.8 (3.4)	600.2
P,PR,RP,TR,BD,SZ	-66.4 (-3.1)	1.4 (2.1)	7.3 (0.4)	0.1 (0.3)	2.6 (6.6)	2.8 (3.4)	600.4
P,PR,TR3,BD3,SZ3	-69.3 (-4.2)	1.1 (1.6)		0.8 (2.1)	2.5 (7.1)	1.6 (2.5)	620.7
P,PR,RP, TR3,BD3,SZ3	-52.1 (-2.4)	1.1 (1.6)	-20.7 (-1.2)	0.7 (2.0)	2.6 (7.1)	1.6 (2.5)	622.2
P,PR,TR5,BD5,SZ5	-67.7 (-4.1)	1.2 (1.8)		0.5 (1.4)	2.6 (7.2)	1.9 (2.7)	617.9
P,PR,RP, TR5,BD5,SZ5	-55.9 (-2.6)	1.2 (1.8)	-14.9 (-0.9)	0.5 (1.3)	2.7 (7.2)	1.9 (2.8)	618.7
P,PR,RP3	-51.8 (-3.8)	1.1 (2.3)	20.8 (1.8)				276.4
P,PR,RP3,IT3	-52.4 (-2.4)	1.2 (1.7)	-4.3 (-0.2)			3.6 (13.0)	642.5
P,PR,TR3,RP3	-55.4 (-3.5)	1.3 (1.9)		0.9 (2.5)	3.2 (10.6)		648.5
P,PR,RP3,TR3,IT3	-58.2 (-2.5)	1.3 (1.9)	3.3 (0.2)	0.9 (2.5)	3.2 (10.6)		648.6
P,PR,RP3, BD3,SZ3	-65.7 (-2.9)	1.1 (1.6)	-4.5 (-0.2)	0.7 (2.1)	2.5 (7.1)	1.6 (2.5)	620.7

Table 5.52 Estimated parameters for aggregated dataset for dishwashing detergent (n=908, nob=12, null log likelihood=-2256.3)

Model	P	PR	RP	Price based	Item based	Chi Squared
P,PR	-3.0 (-3.8)	0.2 (1.7)				485.5
P,PR,RP	-25.4 (-2.8)	0.2 (1.6)	-9.2 (-1.1)			486.8
P,PR,TR	-35.1 (-4.3)	0.2 (1.7)		0.5 (4.8)		508.9
P,PR,IT	-29.3 (-3.4)	0.4 (2.9)			2.5 (28.5)	1412.3
P,PR,TR,IT	-29.4 (-3.4)	0.4 (2.9)		0.0 (0.1)	2.5 (27.9)	1412.3
P,PR,RP,TR,IT	-22.0 (-2.2)	0.4 (2.8)	-14.6 (-1.6)	0.0 (0.1)	2.5 (28.0)	1414.9
P,PR,TR3	-39.6 (-4.8)	0.2 (1.4)		1.0 (11.2)		615.1
P,PR,IT3	-25.4 (-2.9)	0.4 (2.7)			2.6 (30.1)	1517.1
P,PR,TR3,IT3	-27.2 (-3.1)	0.4 (2.8)		0.3 (2.7)	2.5 (28.3)	1524.4
P,PR,RP,TR3,IT3	-12.4 (-1.2)	0.4 (2.7)	-28.5 (-3.1)	0.3 (2.9)	2.5 (28.3)	1533.9
P,PR,TR5	-40.1 (-4.9)	0.3 (1.7)		0.9 (9.3)		576.9
P,PR,IT5	-28.0 (-3.2)	0.5 (2.9)			2.6 (29.3)	1531.5
P,PR,TR5,IT5	-30.2 (-3.4)	0.5 (3.0)		0.3 (2.7)	2.5 (28.1)	1538.8
P,PR,RP,TR5,IT5	-19.1 (-1.9)	0.5 (3.0)	-21.5 (-2.3)	0.3 (2.8)	2.6 (28.2)	1544.2

Table 5.53 Estimated parameters for aggregated dataset for dishwashing detergent with refined measures

Model	P	PR	RP	Price based	Brand based	Size based	χ^2
P,PR,TR,BD,SZ	-28.8 (-3.3)	0.5 (3.2)		0.0 (0.3)			1518.1
P,PR,RP,TR,BD,SZ	-20.4 (-2.0)	0.5 (3.2)	-16.3 (-1.8)	0.4 (0.4)	2.4 (23.0)	1.4 (13.2)	1521.3
P,PR,TR3,BD3,SZ3	-27.9 (-3.2)	0.6 (3.6)		0.3 (2.5)	2.4 (23.4)	1.5 (13.6)	1644.7
P,PR,RP, TR3,BD3,SZ3	-13.4 (-1.3)	0.6 (3.5)	-27.8 (-3.0)	0.3 (2.7)	2.4 (23.4)	1.5 (13.7)	1653.6
P,PR,TR5,BD5,SZ5	-29.8 (-3.4)	0.5 (3.3)		0.3 (2.5)	2.5 (22.9)	1.5 (12.7)	1609.0
P,PR,RP, TR5,BD5,SZ5	-18.8 (-1.9)	0.5 (3.3)	-20.9 (-2.2)	0.3 (2.6)	2.5 (23.0)	1.5 (12.7)	1614.1
P,PR,RP3	-23.9 (-2.5)	0.2 (1.6)	-10.4 (-1.1)				486.8
P,PR,RP3,IT3	-5.2 (-0.5)	0.4 (2.7)	-33.8 (-3.2)		2.6 (30.2)		1527.8
P,PR,TR3,RP3	-27.2 (-3.1)	0.4 (2.8)		0.3 (2.7)	2.5 (28.3)		1524.4
P,PR,RP3,TR3,IT3	-6.0 (-0.6)	0.4 (2.7)	-35.2 (-3.4)	0.3 (2.9)	2.5 (28.3)		1535.9
P,PR,RP3,TR3, BD3,SZ3	-7.2 (-0.7)	0.6 (3.5)	-34.1 (-3.3)	0.3 (2.7)	2.4 (23.4)	1.5 (13.7)	1655.5

Table 5.54 Summary of Predictive Tests on Split Samples

Model	Catsup	Yogurt-Market 1	Yogurt-Market 2	Dishwashing Detergent
(P,PR,IT3)	-210.5	-67.4	-37.6	-572.8
(P,PR,RP3,IT3)	-210.7	-68.6	-38.3	-569.8
(P,PR,TR3,IT3)	-205.1	-65.2	-35.8	-570.8
(P,PR,TR3,BD3, SZ3)	-212.4	-64.2	-47.2	-542.9
Prediction success rate				
(P,PR,IT3)	101/174	59/80	84/93	165/355
(P,PR,RP3,IT3)	99/174	57/80	84/93	165/355
(P,PR,TR3,IT3)	103/174	59/80	83/93	165/355
(P,PR,TR3,BD3, SZ3)	99/174	59/80	83/93	161/355

CHAPTER 6
CONCLUSIONS

The model of consumer price inertia was formulated to address several issues related to the manner in which the effects of price on consumer brand choice have been modelled in the past. The most serious concerns were the relative lack of importance given to individual differences in price sensitivity, and the apparent contradiction between the findings of previous empirical modelling research and descriptive survey research. The former assumed a conscious attempt on the part of consumers to encode price information for all brands and sometimes, to even remember and use this past information to guide their current choices, and the latter usually showed that very negligible, or at the least, very errorful encoding takes place in supermarket aisles. A third concern was that price coefficients in models of choice estimated in the past may have been biased because of the misspecification of the consideration sets for price sensitive consumers

The model of consumer price inertia sought to resolve these problems by specifying an effect of price on choice, which could vary with consumers, which would not require encoding of price information for all brands in the marketplace, and which would allow for differences in consideration sets. In this chapter, the model's performance in terms of addressing these issues will be discussed in the light of the

findings of the empirical studies described in Chapters 4 and 5. Limitations of the research, and future directions pointed to by this research are also discussed.

Individual Differences in Price Sensitivity

One of the major shortcomings of previous empirical modelling research about the effects of price on consumer choice has been the relative neglect of specification of individual differences in price sensitivity. The variables on which individual differences have been specified have usually been brand related constructs such as brand preferences, variety seeking tendencies, brand loyalties, and consideration sets of brands. A good justification for neglecting differences in price sensitivity (apart from considerations of parsimony, which might restrict the number of parameters that might be estimated in a single model) might be that these brand related constructs are conceptually correlated to price sensitivity. Accounting for differences in brand loyalty and brand preferences might thus automatically account for differences in price sensitivity, since consumers who are more brand loyal might justifiably be presumed to be less price sensitive. Also, if different brands are priced at different points on the price continuum, loyalty to a certain brand is akin to loyalty to a certain point on the price continuum. This spurious correlation may have helped previous models in achieving goodness of fit without controlling for individual differences in price sensitivity.

The empirical model of consumer price inertia provides a framework for analyzing the degree to which such a relationship might exist in a relatively

straightforward fashion. Individual differences were specified both in terms of items purchased in the past and prices paid in the past. The correlation matrix of the brand and price based consideration set membership constructs for each of the product categories is presented in Table 6.1. Correlations between the price and brand based consideration set membership variables were very low for both catsup and dishwashing detergent, the highest correlation between the two variables being 0.22 for the three-period measure for catsup and 0.18 for the three-period measure for dishwashing detergent. Thus, for these categories, the predictions of consideration set membership made from observation of prices paid in the past were different from the predictions made from observation of brands purchased in the past. The consideration set membership variable based on prices was significant for both these segments even after controlling for the powerful item based measure, suggesting that either the phenomenon may be occurring interactively with the item based measure (consumers may be using price and brand-sizes to eliminate choices, in a sequential fashion) or that there may be differences among consumers such that some consumers eliminate alternatives based on brand-size and others eliminate alternatives based on prices. For yogurt, the correlations were higher, as high as 0.48 for market 1 and 0.40 for market 2. For this category too, the price based consideration set membership variable was significant after including the item based membership variable. The high correlations suggest that both measures tended to include the same items in the consideration set. This may have partly been because of the higher proportion of size loyal consumers for yogurt, and the existence of

distinct price tiers for the category. For example, among the eight ounce items, there were three that were priced on average around sixty cents and thirteen items priced at around forty cents. For the six ounce items, there was one item priced at 74 cents, three priced at around 60 cents, one at 54 cents, and two priced at around 40 cents (see Appendix D). The other categories did not have a large proportion of consumers who were single-size loyal. It may be recalled that the price-based consideration set membership variable was significant for the single size loyal segment for catsup. For this, the 32 ounce segment, there was some evidence of a price tiered structure, with three items priced at around $1.15, and a store item priced at around ninety cents. For dishwashing detergent, the only size loyal segment of a reasonable size was the 12 ounce segment, and all five 12 ounce alternatives were priced at around 83 cents. Thus, there was no tiered structure in the market for this segment.

Thus, the presence of a price tiered structure and the phenomenon of different segments of consumers purchasing among different items, helps the price based consideration set variable to correctly predict the consideration set. The price tier variable requires the tracking of only one variable, the price paid, rather than the item based variant, which requires tracking all items that are purchased, and hence a set of as many dummy variables as there as items. The price tier variable is thus more parsimonious. The survey of consumers also established the presence of distinct segments of consumers who differ in their reservation prices for all the categories examined.

Thus, the dissertation established the importance of specifying individual differences and showed that specifying differences in terms of acceptable price ranges was a parsimonious and effective way of controlling for these differences.

The Anomalous Findings of Reference Price and Descriptive Survey Research

A second concern with previous choice research which examined the effects of price, and especially the reference price research reviewed earlier in Chapter 2, is that consumers have been assumed to be diligent users of price information across brands and across time. Most descriptive research that has surveyed consumers about their processing of price information, and more generally, about their price knowledge, has revealed considerable individual differences among consumers, and a large amount of error in the encoding of prices. The model of price inertia explains this discrepancy by hypothesizing that while consumers may not track all prices in the marketplace across time, they may have a more stable recall of the prices that they paid for previous purchases in the category. Thus, current brand choice may be a function of prices paid for the category in the past, and not necessarily a function of prices observed for each of the brands in the past. The survey of consumers established that a large number of consumers did recall the last price paid for a purchase in a product category (though it is not known how errorful that recall may have been), and that for a semi-durable category like shirts, price recall may in fact be "better" than brand recall. Thus, price may have strong effects on consumer utility and probability of brand choice, and yet price recall at the brand

level may be weak. The scanner data results revealed that the price based consideration set membership variable was significant in the best fitting model for all product categories, while the reference price measure was not a significant predictor for yogurt, and for one of the two alternate definitions for both catsup and dishwashing detergent. There was little difference between the two measures in predictive ability. The price based consideration set membership variable seems to be a theoretically more attractive variable than the reference price variable since it does not require the assumption of high price involvement. The measure also does not assume an arbitrary functional relationship between prices observed in the past and the current reference price.

Consideration Set Specification

A third problem in estimating the "true" price coefficients from choice models estimated across a panel of consumers and across a period of time, is that the set of brands considered by different consumers may be different, and for the same consumer, the set of brands considered at different times may be different, especially if the price and promotion environment changes across time. Also, since data is often aggregated across stores, factors such as the availability of brands in different stores, the relative prices of the various brands in different stores, the availability of store and generic brands and the display of different brands may differ across stores and hence the consideration set may even differ for the same consumer across stores. A multinomial logit model estimated with the wrong consideration set assumption

could underestimate the magnitude of the true price coefficient since a consumer who chooses only among some of the brands would seem to be ignoring prices and price changes for all the other brands. The price coefficient may be also be biased upward (i.e. consumers may appear to be more price sensitive than they really are), if a majority of consumers switch randomly among the lower priced brands but never purchase the more expensive brands. Since all the models of reference price reviewed earlier assume that the consideration set is fixed across consumers and time and consists of the entire market, the price and reference price coefficients estimated may be subject to these biases. Often, the seriousness of this problem may be ameliorated by the specification of a "brand loyalty" measure, which tracks the tendency to purchase some brands more frequently than others. The price and brand based consideration set membership variables are theoretically more attractive since they do not depend on an arbitrary specification of a brand loyalty measure, and empirically easier to estimate as they do not require a grid search to estimate the best specification for the brand loyalty measure. It may be noted that simple as these measures are, they are powerful predictors, and were shown to predict as high as 89% of the brand choices, in a holdout sample for one of the categories.

Thus, all three concerns with past research that inspired the model of consumer price inertia were resolved to some extent by the findings of the empirical studies conducted in this dissertation.

Product Market Conditions and Choice Parameter Estimates

One of the most significant findings of both the survey research and the panel data analysis was that there were differences across product categories. The survey revealed, for example, that beer and paper towels were more subject to price-quality inferences, as evidenced by a larger proportion of respondents expressing lower bounds. Also, magnitudes of price and brand recall were much closer for paper towels than for the other supermarket categories in the survey. The scanner data analysis revealed strong support for the price based consideration set membership variable for yogurt, presumably because of the strongly price-tiered market. The results were not as strong for the other categories, where there was not as price-tiered a market structure. These results point out to the strong possibility that prior choice research (almost all the reference price research reviewed earlier) which has often been restricted to the then most easily available coffee dataset may be biased by characteristics of the coffee market (few different sizes, frequent promotion, high frequency of purchase, few major brands, etc.). The finding that parameter estimates vary across product categories suggests that a fruitful avenue for future research would be to uncover the relationships between category characteristics and choice parameter estimates.

Limitations

The major limitation of the survey was that since it was conducted over the phone, the accuracy of brand and price recall could not be ascertained. Also, five of

the six product categories investigated were frequently purchased consumer non-durables. The survey results suggest that semi-durable or durable goods may be as good or better categories to study to understand the circumstances under which the relative impact of price on choice may be greater than that of brand names. Finally, verbalized responses to questions about the existence and use of upper and lower acceptable limits on prices for different product categories may not be completely revealing of the extent of this phenomenon, as consumers may either construct these ranges for the purposes of the interview, biasing upward the estimated proportion of consumers with these limits, or may be unable to verbalize the bounds used without the varied cues of an actual supermarket display, biasing the estimated proportion downward. These concerns with the survey research may be resolved by either interviewing consumers in stores or in a laboratory setting. A laboratory setting may also help establish the conditions in the product-market like the number of brands available, the presence of a price-tiered structure, the frequency of promotions and the availability of store and generic alternatives, which are conducive to the development of these acceptable upper and lower bounds.

A limitation of the panel data analysis was that other forms of inertia such as "form" inertia were ignored in the analysis. There may have been segments of consumers loyal to particular variants of the product categories (for example, "fruit on bottom" for yogurt).

A second limitation of the panel data analysis was that the ranges of acceptable prices for consumers were defined on the actual prices paid in the past.

This range may underestimate the actual range as the set of prices paid in the past may not ever include the "true" reservation price or the "true" lower bound of the consumer. A theoretically derived estimate of the acceptable price range based on the prices of all the brands may be a better measure of the acceptable price range. As the number of lags increases in the definition of the acceptable price range, this bias should decrease[5]. Alternate measures of acceptable price ranges (for example, allowing only upper bounds and not lower bounds) may result in different conclusions.

A minor limitation of the scanner data analysis was that only three product categories were studied. A larger set of product categories would allow for a more systematic study of the factors influencing the importance of the price based consideration set variable across product market conditions.

Substantive Implications

In addition to the theoretical implications stressed above, the model of consumer price inertia also has implications for marketing managers and retailers. The most significant long run implication is that frequent price promotions by several brands may have deleterious effects on the entire product category. The model of price inertia stresses that the increased attunement to prices that is caused by the increased attention by both retailers and manufacturers can lead to price dominating

[5]In this respect, it was heartening to note that the seven-period definitions of acceptable price ranges did not perform very differently from the three or five period measures.

the brand names in affecting brand choice. A large proportion of consumers may be encoding alternatives on the shelf in terms of their prices rather than in terms of brand names, leading to erosion of brand equity in the long run. This is in contrast to the models of reference prices that predict decreases in profitability for individual brands that promote often. More product categories would have to be studied to understand the circumstances under which such a phenomenon is most likely to occur.

A practical contribution of the model is the development of a new technique for the evaluation of price promotions and for the prediction of future market share changes resulting from price promotions. Also, the model implies that brand-price combinations (e.g. brand X at price Y) may be more useful units of analysis for evaluating price promotions, as the same brand may be competing with different other brands at different price levels. This evaluation scheme may be a deterrent to the short run orientation of brand managers that results in frequent promotions for short term increases in market share, if shares are computed at the brand level.

Future Research

The limitations mentioned earlier all suggest fruitful areas of future research that will improve upon the model of price inertia. Other research that may be derived from this work is expected to be in the directions listed below.

(i) The concept of price inertia can be generalized to the concept of "choice rule inertia". Consumers may differ in the rules that they use to make choices (some may screen on brand names first, others on price first, still others on other attributes), but the choice rules themselves would be hypothesized to stay stable over time.

(ii) A theorectical exploration of the causes of the differences of the model's (and related models') performance across product categories in terms of the characteristics of these categories such as frequency of purchase, extent of promotional activity, number of brands, presence of private labels/generics, variance of prices across brands and number of package sizes would be a useful step toward developing a theory of product category characteristics and how these characteristics could affect both consumer choice behavior and the parameters of models of choice.

(iii) The distinction drawn between adaptation to price exposure and adaptation to prices paid that distinguish our model from previous reference prices can be tested in an experimental setting in a more controlled fashion.

(iv) Incorporating the model into a normative price setting model would be another useful extension.

Table 6.1 Correlations between variables for the combined datasets

	Catsup	Yogurt Market 1	Yogurt Market 2	Dish Detergent
(TR,IT)	0.19	0.43	0.23	0.14
(TR3,IT3)	0.22	0.45	0.31	0.18
(TR5,IT5)	0.21	0.48	0.30	0.16
(TR3,BD3)	0.11	0.35	0.35	0.14
(TR5,BD5)	0.09	0.37	0.40	0.16
(TR3,SZ3)	0.07	0.33	0.34	0.15
(TR5,SZ5)	0.14	0.37	0.42	0.16

APPENDIX A
RESERVATION PRICES AND THE PROSPECT THEORY HYPOTHESIS: POSTULATE AND PROOF

Postulate : Let consumer i's reservation price be p_i. Let $g(p_i)$ be the probability density function representing the distribution of reservation prices across the population, and $G(p_i)$ be the corresponding distribution function. Let α_k represent the attractiveness of brand k on non-price attributes, and $p_1,p_2,...,p_n$ represent the regular prices of n brands in the market, where brands 1,2,...,n are numbered such that, $p_j \leq p_{j+1}$, for i=1,2,...,(n-1). Then, the loss in market share for brand k, when its price increases by Δ will be greater than the corresponding gain, when the price decreases by Δ, if the density function is upward sloping at p_k. Conversely, the loss in market share will be smaller than the gain in market share if the density function is downward sloping at p_k.

Proof : According to the model of consumer price inertia, consumer i's probability of purchasing brand k will be 0, if $p_k > p_i$, and will otherwise be given by:

$$Prob_{ik} = \frac{\alpha_k}{\sum_{p_j \leq p_i} \alpha_j}$$

Hence, the predicted market share for brand k at price p_k, in this population, will be

$$S_{p_k} = \sum_{l=0}^{n-k} \frac{\alpha_k}{\sum_{j=1}^{k+l} \alpha_j} \left(G(p_{k+l+1}) - G(p_{k+l}) \right)$$

where, by definition,

$$G(p_k) = \int_0^{p_k} g(p_k)\, dp_k, \quad \text{for } k=1,2,,,n,$$

$$G(p_{n+1}) = 1$$

Now, consider the effects of a small increment and decrement of Δ from p_k, so that the rank order of prices of the alternatives does not change.

For price $p_k+\Delta$, the market share will decrease by

$$S_{p_k+\Delta} - S_{p_k} = \frac{\alpha_k}{\sum_{j=1}^{k} \alpha_j} \left(G(p_k+\Delta) - G(p_k) \right)$$

For price $p_k-\Delta$, the market share will increase by

$$S_{p_k} - S_{p_k-\Delta} = \frac{\alpha_k}{\sum_{j=1}^{k} \alpha_j} \left(G(p_k) - G(p_k-\Delta) \right)$$

Consequently, the loss in market share for a price increase of Δ will be greater than the corresponding gain in market share for a price decrease of Δ if

$$G(p_k+\Delta) - G(p_k) > G(p_k) - G(p_k-\Delta),$$

or, equivalently, if $g(p_k)$ is upward sloping at p_k. The converse can be proved in a similar fashion.

APPENDIX B
COPY OF SURVEY QUESTIONNAIRE

The questions about the product purchases were asked after questions about consumer sentiment, and other questions about shopping for clothes added by other researchers. The questions were asked at around the midpoint of a thirty to forty-five minute interview.

>V3< Now I would like to ask you a few questions about products that you have recently purchased. The questions will be repeated for different product categories.

The first set of questions is about ground coffee. In the past month, have you purchased ground coffee in a supermarket ?

<1> Yes
<5> No [goto V4]
<-8> Don't know
<-9> Not available

>V3A< I would like you to think about the last time that you purchased ground coffee at the supermarket. What brand did you buy?

<1> Person knows what brand
<-8> Don't know [goto V3B]
<-9> Not available [goto V3B]

>V3A1< INTERVIEWER: PUT IN BRAND
[allow 15]>V3A2< How certain are you about your response to this question? Are you very certain, somewhat certain, not certain, or not at all certain?

<1> Very Certain
<2> Somewhat Certain
<3> Not Certain
<4> Not At All Certain
<-8> Don't know
<-9> Not available

>V3B< How many pounds of ground coffee did you buy at this last purchase occasion ?

<1> Person knows quantity
<-8> Don't know [goto V3C]
<-9> Not available [goto V3C]

>V3B1< INTERVIEWER: PUT IN QUANTITY
<0-100>

>V3C< What price did you pay per pound of ground coffee on this last purchase occasion ?

<1> Person knows amount
<-8> Don't know [goto V3D]
<-9> Not available [goto V3D]

>V3C1< INTERVIEWER: PUT IN DOLLAR AMOUNT
<0-100>

>V3C2< INTERVIEWER: PUT IN CENTS AMOUNT
<0-99>

>V3C3< How certain are you about your response to this question? Are you very certain, somewhat certain, not certain, or not at all certain?

<1> Very Certain
<2> Somewhat Certain
<3> Not Certain
<4> Not At All Certain
<-8> Don't know

<-9> Not available

>V3D< What is the highest price that you have paid for a pound of ground coffee in the supermarket ?
INTERVIEWER: IF ASKED, THIS MEANS ANY BRAND.

<1> Person knows amount
<-8> Don't know [goto V3E]
<-9> Not available [goto V3E]

>V3D1< INTERVIEWER: PUT IN DOLLAR AMOUNT
<0-100>

>V3D2< INTERVIEWER: PUT IN CENTS AMOUNT
<0-99>

>V3E< If you were shopping in a supermarket today for a pound of coffee, what is the maximum price that you would be willing to pay ?
INTERVIEWER: IF ASKED, THIS MEANS ANY BRAND.

<1> Person knows amount
<-8> Don't know [goto V3F]
<-9> Not available [goto V3F]

>V3E1< INTERVIEWER: PUT IN DOLLAR AMOUNT
<0-500>

>V3E2< INTERVIEWER: PUT IN CENTS AMOUNT
<0-99>

>V3F< Is there a price for a pound of ground coffee that is so low you would be concerned about the quality of the product, regardless of the brand ?

<1> Yes
<5> No [goto V4]
<-8> Don't know [goto V4]
<-9> Not available [goto V4]

>V3F1< What price is that ?
ENTER DOLLAR AMOUNT
<0-50>

>V3F2< ENTER CENTS AMOUNT
<0-99>

>V4< The next set of questions is about paper towels. In the past month, have you purchased paper towels in a supermarket ?

<1> Yes
<5> No [goto V5]
<-8> Don't know
<-9> Not available

The questions were repeated for paper towels, beer, yogurt, dishwashing detergent and men's dress shirt. The sizes of the first three of these products were anchored at a roll of paper towels, a six-pack of 12 ounce cans of beer and an 8 ounce container of yogurt for the questions about the highest price ever paid and the upper and lower bounds. The only questions that were different for dishwashing detergent and men's dress shirt are listed below.

>V7B< What size of dishwashing detergent -small (that is 12 ounce), medium (that is 22 ounce or 32 ounce), large (that is 48 ounce) or extra large (that is 64 ounce)- did you buy at this last purchase occasion?

<1> Small
<2> Medium
<3> Large
<4> Extra large
<-8> Don't know [goto V7C]
<-9> Not available [goto V7C]

>V7D< What is the highest price that you have paid for dishwashing detergent of the same size that you mentioned for your last purchase occasion ?
INTERVIEWER: IF ASKED, THIS MEANS ANY BRAND.

<1> Person knows amount
<-8> Don't know [goto V7E]
<-9> Not available [goto V7E]

>V7D1< INTERVIEWER: PUT IN DOLLAR AMOUNT
<0-100>

>V7D2< INTERVIEWER: PUT IN CENTS AMOUNT
<0-99>

>V7E< If you were shopping in a supermarket today for dishwashing detergent of the same size you did the last time you bought it, what is the highest price you would be willing to pay ?
INTERVIEWER: IF ASKED, THIS MEANS ANY BRAND.

<1> Person knows amount
<-8> Don't know [goto V7F]
<-9> Not available [goto V7F]

>V7E1< INTERVIEWER: PUT IN DOLLAR AMOUNT
<0-500>

>V7E2< INTERVIEWER: PUT IN CENTS AMOUNT
<0-99>

>V7F< Is there a price for dishwashing detergent of the same size as you mentioned for your last purchase occasion that is so low that you would be concerned about the quality of the product, regardless of the brand?

<1> Yes
<5> No [goto V8]
<-8> Don't know [goto V8]
<-9> Not available [goto V8]

>V7F1< What price is that ?
ENTER DOLLAR AMOUNT
<0-50>

>V7F2< ENTER CENTS AMOUNT
<0-99>

>V8< The next set of questions is about men's dress shirts. In the past month, have you purchased men's dress shirts ?

<1> Yes
<5> No [goto V9]
<-8> Don't know
<-9> Not available

>V81< I would like you to think about the last time that you purchased men's dress shirts. At what store did you make your purchase ? [allow 20]

===>

The section on product purchases concluded with these questions.

>V9< Which supermarket do you usually shop at for groceries?

<1> Person knows store
<-8> Don't know [goto V10]
<-9> Not available [goto V10]

>V9A< INTERVIEWER: PUT IN STORE
[allow 15]

>V10< Could you tell me if you are the main food shopper in your household?

<1> Yes
<5> No
<-8> Don't know
<-9> Not available

APPENDIX C
SHARES AND PRICES OF BRANDS ANALYZED FOR CATSUP

#	Brand	Size (oz)	Market Share (%)	Mean unit price ($/oz)	SD of unit price ($/oz)	Mean price ($)
1	Hunt's (plastic/glass)	32	14.6	0.036	0.006	1.16
2	Hunt's (plastic/glass)	44	1.5	0.043	0.004	1.90
3	DelMonte(plastic)	28	1.5	0.048	0.006	1.35
4	DelMonte(glass)	32	6.7	0.036	0.007	1.15
5	Heinz(glass)	14	2.4	0.057	0.003	0.80
6	Heinz(plastic)	28	16.3	0.049	0.007	1.37
7	Heinz(glass)	32	36.8	0.036	0.005	1.17
8	Heinz(plastic)	40	4.1	0.049	0.005	1.95
9	Heinz(glass)	44	3.0	0.045	0.002	1.99
10	Heinz(plastic)	64	3.8	0.046	0.002	2.94
11	Store(glass)	28	1.6	0.038	0.005	1.07
12	Store(glass)	32	7.8	0.028	0.003	0.88

APPENDIX D
SHARES AND PRICES OF BRANDS ANALYZED FOR YOGURT

#	Brand	Size (oz)	Market Share (%)	Mean unit price ($/oz)	SD of unit price ($/oz)	Mean price ($)
1	Dannon (low fat)	8	21.3	0.080	0.008	0.64
2	Yoplait (custard)	6	8.4	0.105	0.010	0.63
3	Yoplait (original fruit)	6	9.7	0.104	0.011	0.62
4	Yoplait (non fat, fruit on bottom)	6	1.9	0.108	0.013	0.65
5	Yoplait (yo-creme dessert fruit)	5	1.1	0.134	0.010	0.67
6	Swiss Valley Farms (low fat fruit)	8	2.4	0.046	0.005	0.37
7	Well's Blue Bunny (low fat and fruit)	8	5.7	0.054	0.007	0.43
8	Nordica (low fat Swiss fruit)	6	5.3	0.069	0.008	0.41
9	Nordica (low fat, fruit on bottom)	6	2.1	0.070	0.008	0.42
10	Quality (cherry,low fat, fruit)	8	1.8	0.051	0.005	0.41
11	Quality (cherry, fruit)	8	1.3	0.053	0.011	0.42
12	Weight Watcher's (non fat, fruit)	8	10.8	0.077	0.006	0.62
13	Store	8	13.8	0.046	0.005	0.37

APPENDIX D (Continued)

#	Brand	Size (oz)	Market Share (%)	Mean unit price ($/oz)	SD of unit price ($/oz)	Mean price ($)
14	Elm Grove (low fat, Swiss, fruit on bottom)	8	0.9	0.040	0.004	0.32
15	Dannon (fresh flavor, low fat)	8	1.0	0.079	0.009	0.63
16	Dannon (fresh flavor, low fat)	16	0.4	0.073	0.007	1.16
17	Dannon (maple,low fat,fruit on bottom)	4.4	0.6	0.367	0.034	1.61
18	Yoplait (breakfast fruit)	6	0.5	0.122	0.011	0.73
19	Hawthorn Melody (low fat, Swiss fruit)	8	2.4	0.039	0.004	0.31
20	Yami (fruit on bottom)	8	1.6	0.052	0.014	0.42
21	Hiland (low fat, fruit)	8	4.1	0.053	0.011	0.42
22	Store	8	1.1	0.044	0.008	0.35
23	Store	8	1.1	0.048	0.006	0.38
24	Store	6	0.3	0.089	0.010	0.54
25	Store	8	0.7	0.049	0.001	0.39

APPENDIX E
SHARES AND PRICES OF BRANDS ANALYZED FOR DISH DETERGENT

#	Brand	Size (oz)	Market Share (%)	Mean unit price ($/oz)	SD of unit price ($/oz)	Mean price ($)
1	Ivory	12	3.5	0.070	0.002	0.84
2	Ivory	22	9.0	0.058	0.005	1.28
3	Ivory	32	6.5	0.056	0.005	1.81
4	Ivory	48	1.5	0.056	0.003	2.67
5	Joy	12	5.4	0.070	0.001	0.84
6	Joy	22	8.4	0.058	0.003	1.27
7	Joy	32	3.2	0.058	0.003	1.87
8	Joy	48	0.7	0.058	0.003	2.77
9	Ajax	22	2.0	0.061	0.006	1.35
10	Ajax	32	1.7	0.058	0.005	1.85
11	Dermassage	22	0.5	0.046	0.002	1.02
12	Dermassage	32	1.9	0.046	0.003	1.48
13	Palmolive	12	3.0	0.069	0.002	0.83
14	Palmolive	22	6.2	0.054	0.007	1.18
15	Palmolive	32	1.8	0.056	0.006	1.79
16	Palmolive	48	0.8	0.055	0.005	2.66
17	Dove	32	0.4	0.050	0.003	1.59
18	Lux	22	1.2	0.041	0.005	0.91

APPENDIX E (Continued)

#	Brand	Size (oz)	Market Share (%)	Mean unit price ($/oz)	SD of unit price ($/oz)	Mean price ($)
19	Lux	32	1.8	0.046	0.003	1.46
20	Dawn	12	6.8	0.070	0.001	0.84
21	Dawn	22	9.0	0.059	0.005	1.30
22	Dawn	32	2.2	0.058	0.004	1.84
23	Dawn	48	1.3	0.058	0.003	2.77
24	Sun	12	4.0	0.067	0.007	0.80
25	Sun	22	8.0	0.054	0.008	1.20
26	Sun	32	7.1	0.052	0.007	1.66
27	Sun	48	2.1	0.042	0.006	2.06
28	Store	32	0.0	0.034	0.004	1.10
29	Generic	32	0.0	0.017	0.002	0.56

APPENDIX F
SPECIAL PROPERTY OF COEFFICIENTS OF DUMMY VARIABLES IN LOGIT MODELS

The logit model specifies the probability of purchasing an item in the easily interpretable "us"/("us" + "them") form. This special form leads to an interesting interpretation for the coefficient of dummy variables estimated for the random utility model. One of these properties and its proof are given below.

Property. Extremely large coefficients estimated for dummy variables may be interpreted as approximating phased decision making, with the dummy variable being the basis for eliminating alternatives.

Proof : Consider a choice set with n alternatives, and the following utility function:

$$u_j = \alpha_j + \beta d_j + \epsilon_j ,$$

where

α_j = brand specific constant for brand j,

d_j = dummy variable taking value 1 or 0, and,

u_j = utility of brand j.

For convenience, let $d_i = 0$ for brands i=1,2,...,k, and $d_i = 1$ for brands k+1, k+2, ..., n. Then, for brands i=1,2,...,k, the logit model predicts the probability of choice, as

$$Prob_i = \frac{e^{\alpha_i + \beta d_i}}{\sum_{l=1}^{n} e^{\alpha_l + \beta d_l}} .$$

Hence,

$$LIM_{\beta \to \infty} \; Prob_i = LIM_{\beta \to \infty} \frac{e^{\alpha_i}}{\sum_{l=1}^{k} e^{\alpha_l} + \sum_{l=k+1}^{n} e^{\alpha_l + \beta}}$$

$$= 0, \; as \; \beta \to \infty .$$

For brands i=k+1,k+2,...,n, the logit model predicts the probability as,

$$LIM_{\beta \to \infty} \; Prob_i = LIM_{\beta \to \infty} \frac{e^{\alpha_i + \beta}}{\sum_{l=1}^{k} e^{\alpha_l} + \sum_{l=k+1}^{n} e^{\alpha_l + \beta}}$$

$$= LIM_{\beta \to \infty} \frac{e^{\alpha_i}}{\sum_{l=1}^{k} e^{\alpha_l - \beta} + \sum_{l=k+1}^{n} e^{\alpha_l}}$$

$$= \frac{e^{\alpha_i}}{\sum_{l=k+1}^{n} e^{\alpha_l}} .$$

Thus, the alternatives for which d=0 have close to zero probability of being chosen, and choice is restricted to alternatives for which d=1. Thus, extemely large values for β approximate an elimination process in which d serves as the basis of elimination.

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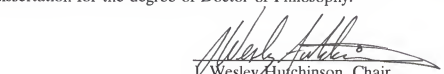
Seshan Ramaswami was born in Bombay on April 10, 1965, to Ananthanarayanan and Banumathi Seshan. He had his schooling at Don Bosco High School, Bombay, from where he graduated in 1980. The next five years were spent at St. Xavier's College, University of Bombay. He secured his Bachelor of Science degree with a major in Mathematics, in 1985. Ramaswami then earned a post graduate diploma in management with majors in Marketing and Information Systems at the Indian Institute of Management, Ahmedabad, in 1987. He worked for a year as a Research Executive at MARG Marketing and Research Group, Bombay, before joining the PhD program in marketing at the University of Florida in August, 1988. In June 1992, Ramaswami accepted a position as Lecturer in marketing at the School of Business and Management in the Hong Kong University of Science and Technology.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.



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